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# The effects of major life events and exposure to adverse environmental conditions on health and health-related outcomes

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# Abstract

This dissertation is comprised of four chapters that examine the effects of major life events and exposure to adverse environmental conditions on health and health-related outcomes. The objective of this work is to establish causal relationships using quasi-experimental methods and mobilising different sources of micro-level data from France.

In the first two chapters, I consider the impact of retirement and the dissolution of a romantic partnership - both important events that occur in the lives of many if not most adults - on income and diet and discuss the potential health effects of these changes. In the first chapter, which is joint work with Olivier Allais and Pascal Leroy, we show that households significantly decrease both their expenditure on food and the amount of food purchased at the time of retirement. This is contrary to the popular hypothesis that retired individuals modify their purchasing behaviours without decreasing their level of actual food intake. We find larger declines in food purchases in households with lower pre-retirement income, suggesting that the savings and social safety net resources of these households do not allow them to smooth consumption upon retirement. The decrease in food quantities purchased appears to be driven by a decline in purchases of food from animal origins, which is likely to undermine the diet balance of retirees.

In the second chapter, I show that household income and food purchases decrease suddenly and significantly upon the dissolution of a romantic partnership and remain below pre-separation levels for several years thereafter. My results point toward low-income households being particularly vulnerable as they appear less able to smooth necessary consumption. While the decline in income is more pronounced for households with higher pre-separation income, I find that the declines in food purchases and body weight mainly affect households in the lowest pre-separation income tercile. The potential health effects are ambiguous as weight loss may have health benefits while an increase in the ratio of unhealthy food purchased may have negative health consequences.

In the third chapter, co-authored with Olivier Allais and Guy Fagherazzi, we investigate the health consequences of exposure to adverse conditions related to World War II during childhood on adult health outcomes. We find that an increase in the intensity of exposure to WWII warfare as measured by the number of French military casualties in the postcode area of birth leads to worse health outcomes at adulthood. Our findings suggest that the effects of war on human capital are long-lasting. This stands in contrast to the effects of war on physical capital, which have been shown to be relatively short-lived. We find effects only for individuals exposed during the first five years of life and thus provide evidence for a critical or sensitive period of development during which individuals appear to be particularly vulnerable to negative experiences.

In the fourth chapter, I consider the effects of exposure to ambient air pollution on health care use and costs. I find that short-term exposure to higher levels of air pollution leads to significant increases in health care expenditure. These costs are the result of exposure to pollution levels that are mostly well below the current regulatory levels. In addition, the estimates reflect only the costs of short-term exposure to air pollution while the potentially even larger effects of long-term exposure are not considered. These high costs from short-term exposure alone suggest that there are considerable benefits to reducing air pollution even further below current limit values. I also find significant heterogeneity of effects across patient characteristics and postcode areas, suggesting that air pollution reduction policies have the potential to reduce health inequalities.

# Introduction

Our life experiences and the general environmental conditions to which we are exposed shape our minds and bodies. Understanding how major life events and environmental conditions affect our behaviour and influence our well-being is essential, as this knowledge can be used to improve our lives. However, estimating the causal effects of these events and conditions on any outcome of interest is difficult due to endogeneity problems and often a lack of adequate data. In the literature, we most often see estimates that capture correlations rather than causal relationships. Many existing studies are based on cross-sectional analyses, often without including an adequate control group and without sufficient information on important confounding factors such as individual and family characteristics, resulting in potentially biased estimates. Even when panel data are used, many studies do not rigorously account for the possibility that unobserved variables may affect both the outcome variable and the probability of exposure to the event or condition, which may still lead to bias in the estimates. Given this potential bias in the estimated effects, these correlational studies have limited informative value.

My aim in this dissertation is to come as close as possible to establishing a *causal relationship* between exposure to selected life events or environmental conditions and health outcomes or health-related outcomes more generally. To this end, I apply a range of quasi-experimental methods and draw on various micro-level data sources from France. Each of the four chapters that compose this dissertation is a stand-alone, independent piece of research that addresses distinct policy-relevant issues. In the first two chapters, I consider the impact of retirement and the dissolution of a romantic partnership, respectively, on income and diet and discuss the potential health effects of these changes. In the third chapter, I investigate the consequences of exposure to adverse conditions related to World War II during childhood and adolescence on health outcomes in adulthood. In the fourth chapter, I consider the short-term effects of exposure to ambient air pollution on health care use and costs.

Knowledge of the impact of key life events on health and health-related outcomes is crucial for policy considerations. The study of retirement is particularly relevant in the current context of ageing populations (United Nations, 2017). The proportion of individuals aged 60 years or older in Europe is projected to increase to 35% by 2050. It has been shown that adequate nutrition is important to avoid or postpone the onset of certain diet-related chronic diseases and cognitive decline, as well as conditions such as frailty in older individuals (World Health Organization, 2015). Health policies to avoid or postpone the onset of chronic diseases and care-dependency could not only increase the well-being of the concerned elderly individuals, but it could also help to curb costs in health care systems that are already under strain. A correct measure of how retirement impacts diets and health is helpful to orient policymakers designing and targeting of such health policies.

The large and growing number of people affected by the breakup of a romantic relationship makes the study of this life event also highly relevant from a policy perspective. In France, the share of cohabiting couples who broke their first union before eight years of life together more than doubled from 12% for unions formed between 1970 and 1978 to 29% for those formed between 1997 and 2005. Cross-sectional data show that the average standard of living per person in single-parent families is one-third lower than the average for other families. This has important implications for public policy, given that lower economic resources are associated with worse adult and children's outcomes, including poorer psychological and physical health, lower academic achievement, and more behavioural problems (Amato, 2000, 2014; McLanahan et al., 2013; Tach and Eads, 2015). Well-targeted policies supporting temporarily vulnerable families are likely to avoid costly adverse outcomes in the future (OCDE, 2011) but necessitates adequate information on how and when precisely families are affected. However, the majority of the studies on the effects of retirement or the breakup of a romantic relationship on economic and health outcomes establish associations rather than causation which limits their informative value for policy recommendations.

Exposure to particular experiences and environmental conditions influence health development at all life stages, but it has been shown that exposure during childhood and adolescence has particularly powerful and long-lasting consequences on health due to the persistence of bio-behavioural attributes that are acquired early in life (Almond and Currie, 2011; Baird et al., 2017; Cunha and Heckman, 2007; Fall and Kumaran, 2019; Halfon and Hochstein, 2002; Hertzman, 1999). Exposure to extreme adverse conditions such as war-related hardship is likely to have devastating and potentially long-lasting effects on the health of wartime children. Yet, there has been only limited research exploring how early-life exposure to war affects long-term health outcomes in the civilian population. Knowing more

about the impact of early childhood conditions on adult health outcomes offers insights into prevention, diagnosis and intervention.

Finally, my study of the health effects of ambient air pollution is motivated by the fact that air pollution is the most important environmental risk to the health of Europeans (EEA, 2020). It is often argued that air quality standards are set somewhat arbitrarily, with inconclusive evidence of the health benefits and inadequate consideration of the costs borne by producers and consumers. The potential heterogeneity of effects is rarely explored in a systematic way. Accurate information on the benefits of reducing air pollution is critical in determining the optimal level of environmental policy, particularly in cases where pollution levels are already relatively low, and further pollution reductions are likely to be costly. I estimate the causal effects of air pollution on health care use and costs in France, where pollution levels are on average below the current limit values.

The exact contributions of this dissertation to the existing literature differ depending on the life event or environmental conditions in question and are detailed in the following summary of the dissertation chapters.

## Chapter 1: Changes in food purchases at retirement in France

The first chapter of this dissertation is co-authored with Olivier Allais and Pascal Leroy and has been published in *Food Policy* (2020)[1]. In this chapter, we study the effects of retirement on food consumption and nutrition in France.

Previous research shows that households significantly reduce their food expenditure upon retirement (Haider and Stephens, 2007; Fisher et al., 2008; Hurst, 2008; Battistin et al., 2009; Miniaci et al., 2010; Aguila et al., 2011; Barrett and Brzozowski, 2012; Luengo-Prado and Sevilla, 2013; Moreau and Stancanelli, 2015; Li et al., 2015; Stephens and Toohey, 2018). This result has been called a "retirement (food) consumption puzzle" because it contradicts the implications of the standard life-cycle consumption model, which predicts that forward-looking agents smooth their consumption over their lifetime to avoid fluctuations induced by predictable income changes such as reduced income at retirement (Friedman, 1957; Modigliani and Brumberg, 1980). However, a decrease in food expenditure does not

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necessarily indicate that the quantities consumed are changing to the same extent. Households may spend less on food but maintain the total amount of food consumed by adjusting their choices in the quality and variety of food purchased. After retirement, newly cash-poor but time-rich households can spend more time shopping for bargains or preparing time-consuming and cheaper meals at home (Hurst, 2008; Stancanelli and Van Soest, 2012). Empirical evidence for this theory has been presented in Aguiar and Hurst (2005) for the US and in Chen et al. (2017) and Dong and Yang (2017) for China. Yet, recent work by Stephens and Toohey (2018), who expanded upon the influential Aguiar and Hurst (2005) study challenged these results, finding that caloric and nutrient intake falls at retirement.

We contribute to this ongoing debate on the "retirement (food) consumption puzzle" by assessing the impact of retirement on food consumption both in terms of food expenditure and actual quantities purchased. We use detailed home-scan data on all food items purchased by a representative panel of French households from *Kantar Worldpanel* covering the period 2005 to 2014. Exploiting the longitudinal aspect of the data, we implement a household fixed effect model that allows us to control for *time-invariant* household characteristics. Along with Stephens and Toohey (2018), our study is one of the first to use longitudinal data to more rigorously investigate the impact of retirement on food consumption. We further consider the possibility that our estimates may still be biased if *time-varying* household characteristics are correlated with retirement status and food consumption. We address this endogeneity issue by using the legal minimum age for retirement as an instrument for retirement status. The identification strategy rests on the fact that reaching the minimum legal age for retirement, and thus becoming eligible to pension benefits, exerts a powerful influence on the individual's decision to retire (Diamond and Gruber, 1999). This discontinuous incentive in retirement schemes provides an exogenous shock on retirement behaviour which we exploit to estimate the causal impact of retirement on food purchases.

In addition to studying overall food expenditure and quantities purchased, we divide food products into 6 groups, considering similarities in nutritional content and consumer preferences. The definition of these food groups is useful to study the evolution of diet patterns at the time of retirement. As the nutritional composition of foods differs between food groups, relative changes in the amounts purchased from these groups imply different changes in nutrient intakes. It is useful to know how nutrient intakes vary to infer health effects. To my knowledge, there is no existing study using European data that examines the causal impact of retirement on the whole diet at the level of food categories.

We find that households significantly decrease their expenditure on food and the

amount of food purchased upon retirement. The decline in expenditure is roughly proportional to the decline in quantities purchased. Supposing that households consume what they purchase, this suggests that retirement does not only lead households to spend less money on food but they are also consuming a smaller quantity of food. This goes against the assumption that retirees modify their purchasing behaviour without reducing their actual food consumption. These results are evidence of the existence of the "retirement (food) consumption puzzle". In addition, we find larger declines in food purchases among households with low pre-retirement incomes, suggesting that these households' savings and social safety net resources do not allow them to smooth their consumption in retirement. This indicates welfare losses that may be addressed by appropriate policy intervention. Finally, our results indicate that the decrease in food purchases that we see at the aggregate level is due to a decrease in purchases of animal-based food products. This results in a reduced intake of saturated fatty acids and salt, which can have positive health effects, but also reduces the intake of health-promoting nutrients such as protein, calcium and vitamins.

## Chapter 2: Broken homes and empty pantries: The impact of romantic relationship dissolution on household economic resources

In this chapter, I examine the impact of a couple's break-up on the household's economic resources by studying changes in income and food purchases around the time of break-up in a panel of French households. To infer potential health effects, I look at changes by food group to track dietary patterns and assess whether these changes translate into changes in the body weight of household members.

The economic consequences of union dissolution have been studied many times, showing evidence of a drop in income one year after a divorce ranging from 23% to 40% (Hoffman, 1977; Duncan and Hoffman, 1985b; Bianchi and McArthur, 1991; Holden and Smock, 1991; McLanahan and Sandefur, 1994; Peterson, 1996; Galarneau and Sturrock, 1997; McKeever and Wolfinger, 2001; Avellar and Smock, 2005; Tach and Eads, 2015). In most studies, the effects have been estimated by comparing changes across two time periods, before and after the break-up occurs. However, estimates based on simple "before and after" comparisons are likely to be biased if the effect is not immediate and constant over time. Besides, many of these studies do not include a control group. With respect to dietary patterns, a few studies

examine associations between changes in marital status and dietary behaviours, focusing on a limited set of food items (Lee et al., 2004; Vinther et al., 2016).

I use data on a panel of French households from *Kantar Worldpanel* to investigate the impact of a couple's break-up on household income and food purchases as proxies for household economic resources. I estimate a household fixed effects model to account for unobserved time-invariant household characteristics and control for a range of time-varying household covariates, including the employment status of both spouses. I examine changes in income and food purchases in the years shortly before, during and after the break-up relative to a reference period of three years or more before the event to account for the possibility of adjustments over time to changes in relationship status.

I am not aware of any study investigating the time-path of income and diet following the break-up of a romantic relationship in France. Dynamic adjustments to changes in relationship status are rarely investigated as the necessary longitudinal data on a large representative number of households are not readily available. Some few studies have used longitudinal data to investigate the time-path of income and consumption after separation but have either not controlled for time-varying household characteristics or do not account for unobserved heterogeneity (Fisher and Low, 2016; De Vaus et al., 2014, 2017; Fisher and Low, 2009). A notable exception is a study by Page and Stevens (2004) using U.S. data in which changes in household income and food expenditures after a couple's breakup are estimated using household fixed-effect models and controls for additional time varying covariates. Unlike any previous research I am aware of, I further examine whether the changes in food purchases translate into changes in the household member's body weight or changes in the quality of their diets in terms of the share of unhealthy food products purchased.

I find that household income and food purchases decrease suddenly and significantly at the time of break-up and remain lower than pre-separation levels for several years after the break-up. The decrease in food purchases appears to translate into a slight decrease in the body weight of the newly single female. I also find that the ratio of unhealthy food purchases relative to total food purchases increases around the time of break-up, suggesting that households adopt less balanced diets. While weight reduction may have health benefits, the adoption of less balanced diets is likely to have negative health consequences. My results indicate that low-income households are particularly vulnerable, as they appear less able to smooth their consumption: While the decline in income is more pronounced for households with higher pre-separation income, I find that the decline in food purchases and body weight

primarily affects households in the lowest pre-separation income tercile. If we assume that preferences for weight loss or the incidence of separation-related depression do not differ across households with respect to pre-separation income levels, finding stronger declines in food purchases and female partner's BMI in the poorest tercile of the households but not in the richest tercile suggests that these changes are due to insufficient financial resources.

My results underscore the importance of investigating not only household income but also household consumption to determine which households are particularly vulnerable to post-separation economic hardship. Changes in food purchases are arguably a more direct measurement of changes in economic resources than changes in income because food purchases are informative about a household's ability to maintain a certain level of necessary expenditures.

## Chapter 3: The long-run effects of war on health: Evidence from World War II in France

The third chapter of this dissertation explores the effects of exposure to World War II warfare during childhood and adolescence on adult health outcomes. This chapter is co-authored with Olivier Allais and Guy Fagherazzi and has been published in *Social Science & Medicine* (2021)[2].

Although exposure to particular environments and experiences appear to influence health development at all stages in life, it has been suggested that exposure to environmental insults during childhood and adolescence has particularly powerful and long-lasting consequences on health due to the persistence of bio-behavioural attributes that are acquired early in life. Many studies examine the relationship between early living conditions and health during adulthood using cohorts exposed to historical events as a natural instrument. Several articles have been written on the impact of exposure to WWII, mostly on the effect of the war-related famine. However, most of these studies establish (non-causal) associations (Elias et al., 2004, 2005; Dirx et al., 1999, 2001; van den Brandt et al., 2002; Portrait et al., 2011; Koupil et al., 2007; Sparén et al., 2004; Havari and Peracchi, 2017).

We use data from the French prospective cohort study E3N on over 28,000 women employed in the French National Education (mainly teachers) born between 1925 and 1950.

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We combine this demographic and health data with historical data on French military casualties, French prisoners of war (POW) and the Allied bombing of France during WWII. In contrast to most of the existing studies which rely on self-reported health outcomes, we use data on objectively measured incidence of cancer, hypertension, angina, myocardial infarction, diabetes and obesity. We are also able to distinguish the effects of war-related hardship as captured by our measures of warfare based on the historical data from the effect of nutritional shortages because we have information on the level of hunger suffered during WWII as reported by the study participants.

To establish causality, we exploit variation in the intensity of the war across time and space which is plausibly exogenous to individual and family characteristics. We compare health outcomes for women born in postcode areas that were intensely affected by the war with women belonging to the same group of birth cohorts but who were born in less affected postcode areas, relative to women from other birth cohorts. Identification strategies of this type are often used in the quasi-experimental literature but exploiting data at a geographic level as fine as the postcode code area is less common. Our work is closest to Akbulut-Yuksel (2017) who also uses data at a fine geographical level and employs a similar identification strategy to study the effects of early-life exposure Allied bombing on adult health in Germany. An important caveat of this study, however, is that it exploits data on residence during adulthood and not birthplace, which is likely to compromise the identification strategy. A few other studies use similar identification strategies at a fine geographical level but with different focus. For example, Schiman et al. (2019) do not study the effects of warfare, but rather the war-induced rise in infant mortality while Conti et al. (2019) focus on prenatal exposure.

We find that an increase in the intensity of exposure to WWII warfare as measured by the number of French military casualties in the women's postcode area of birth leads to worse health outcomes at adulthood for those who have experienced exposure during the first five years of their life. The results are robust to the inclusion of the observed health-affecting behaviours (tobacco consumption, sleep duration, and diet) which suggests that the effects are not mediated through changes in these health behaviours. Our results also remain unchanged when we control for the level of hunger suffered during World War II as reported by the study participants, indicating that the effects we capture through our measures of war exposure are distinct from the effects of war-related nutritional shortages.

The results from our study suggest that the effects of war on some forms of human capital are long-lasting which stands in contrast to the effects of war on physical capital,

which have been shown to be relatively short-lived (Bellows and Miguel, 2009; Brakman et al., 2004; Davis and Weinstein, 2002; Miguel and Roland, 2011). The fact that we find effects only in those exposed during the first five years of life suggests that there is a critical or sensitive period of development during which individuals are more vulnerable to negative experiences. The existence of critical or sensitive periods is still highly debated in the literature and our results contribute to this debate by providing new empirical evidence. Our findings underline the importance of post-conflict policies primarily targeting children exposed during early childhood to mitigate, or potentially reverse, the adverse long-term health effects caused by exposure to war.

## Chapter 4: Putting a price tag on air pollution: the social health care costs of air pollution in France

In the last chapter of this dissertation, I study the effects of air pollution on health care use and costs in France. This chapter is my most recent working paper and my "job market paper".

Exposure to air pollution has well-documented adverse effects on human health such as increased risk of cardiovascular and respiratory disease and cancer. In 2016, air pollution was estimated to contribute to 7.6% of worldwide deaths (WHO, 2017). In response, many countries have put in place air quality standards and objectives for a number of pollutants present in the air. Yet, it is often argued that these standards are set arbitrarily, without conclusive evidence of health benefits to be weighed against the costs of pollution reduction to producers and consumers. Accurate information about the benefits of reduced air pollution matters greatly for determining the optimal level of environmental policy and particularly so in the context of developed countries where pollution levels are already relatively low and further pollution reductions likely to be costly. I estimate the causal effects of air pollution on health care use and costs in France where pollution levels are mostly situated below the current limit values.

Estimating the causal effect of air pollution on health care costs is difficult due to problems of endogeneity and a general lack of adequate data. In the past decade, researchers have employed quasi-experimental designs that use a plausible exogenous source of pollution variation to estimate the causal effects of air pollution on health. However, these studies are usually limited to relatively narrow geographical areas and time periods, consider only

a specific part of the population - most often children or the elderly - or study the effects of pollution on a limited selection of health conditions (Anderson, 2015; Schlenker and Walker, 2015; Knittel et al., 2016; Arceo et al., 2016; Deryugina et al., 2016; Schwartz et al., 2016; Ebenstein et al., 2016; Deschênes et al., 2017; Bauernschuster et al., 2017; Deryugina et al., 2019; Godzinski and Suarez Castillo, 2019). Much of the existing work considers mortality, a rather extreme event that is less likely to occur following exposure to moderate levels of air pollution.

To the best of my knowledge, this is the first quasi-experimental study to comprehensively quantify the health care costs caused by exposure to moderate levels of air pollution in a nationwide representative sample. I combine unique administrative data on daily health care reimbursements for a representative sample of the French population with fine-grained reanalysis data on daily pollution levels and meteorological conditions, and hand-collected data on public transport strikes. I adopt an instrumental variable (IV) approach where I use as IVs the daily variation in the intensity of air pollution at the postcode area level induced by variation in wind speed, wind direction and periods of strike in the public transport sector. The identifying assumption is that variation in pollution due to changes in wind speed, wind direction or public transport strikes is unrelated to changes in health care use or costs except through the influence on air pollution. This should be the case after flexibly controlling for various time and location fixed effects and several additional covariates such as climatic conditions. Wind direction and common levels of wind speed are unlikely to have a direct effect on health care use other than through the effect on air pollution. I do not find evidence for increased health care use on days of high wind speed. Concerning public sector strikes, the exclusion restriction should hold at least for some selected medical specialties such as cardio-vascular and respiratory care which I can analyse separately.

I estimate that a 1µg/m3 increase in daily NO2 and O3 translates into an increase in health expenditure equivalent to €2.5 billion per year. The estimates reflect only the costs of short-term exposure to air pollution while the potentially even larger effects of long-term exposure are not considered. Yet, these high costs from short-term exposure alone suggest that there are considerable benefits to reducing air pollution even further below current limit values. My estimates are several orders of magnitudes larger than estimates from cost-benefit studies (see for example Fontaine et al. (2007); Rafenberg (2015); Pimpin et al. (2018)). While these studies clearly state that their health care cost estimates are conservative, the extent to which total effects have been underestimated has been unknown. My estimates allow to put into perspective by just how much total health care costs have been underestimated to date.

The study also provides evidence for significant heterogeneity of effects across patient and location characteristics. For example, the effects of increased NO2 and O3 pollution on health expenditures are 4 to 6 times stronger in the most unequal postcode areas compared to the effect in the most equal postcode areas (as measured by the Gini Index). This suggests that air pollution reduction policies have the potential to reduce health inequalities.

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# Chapter 1

# Changes in food purchases at retirement in France

with Olivier Allais and Pascal Leroy

**Abstract**

We estimate the impact of retirement on food expenditure and food quantities purchased, using detailed home-scan panel data on food purchases and household characteristics in France. We identify a causal relationship by exploiting the French legal minimum age for retirement as an exogenous shock to retirement behaviour. Upon retirement, households significantly decrease their expenditure on food and the amount of food purchased. Households with lower pre-retirement income appear to be more severely affected. Our results indicate that the decrease in food quantities purchased at the aggregate level is driven by a decline in purchases of food from animal origins. A reduced consumption of animal based food products is likely to undermine the diet balance of retirees.

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# 1. Introduction

Population ageing is one of the most significant social transformations of the twenty-first century. In Europe, 25% of the population is already aged 60 years old or over and this proportion is projected to reach 35% in 2050 (United Nations, 2017). An issue of increasing concern for public policy is how this growing part of the population is affected by transition to retirement. In this paper, we explore the effects of retirement on food consumption and nutrition in France. According to the World Health Organization report on ageing and health (World Health Organization, 2015, p. 70), maintaining adequate nutrition in older age is important in order to prevent or postpone the development of non-communicable diseases (NCD) as well as to reverse or delay declines in capacity and conditions such as frailty. Knowing how retirement impacts food consumption and nutrient intakes would allow policy makers to develop and correctly target preventive health policies. Besides potential improvements in the well-being of the concerned individuals and families, such policies seem particularly necessary in a context of growing public health service costs associated with the treatment of chronic health conditions and elder care.

The vast literature on the impact of retirement on household consumption shows that households substantially reduce food expenditures upon retirement (Haider and Stephens, 2007; Fisher et al., 2008; Hurst, 2008; Battistin et al., 2009; Miniaci et al., 2010; Aguila et al., 2011; Barrett and Brzozowski, 2012; Luengo-Prado and Sevilla, 2013; Moreau and Stancanelli, 2015; Li et al., 2015; Stephens and Toohey, 2018). This result has been named the "retirement (food) consumption puzzle" because it stands in contradiction to the implications of the standard life-cycle model of consumption which predicts that forward looking agents will smooth their consumption over their lifetime to avoid fluctuations induced by predictable income changes (Friedman, 1957; Modigliani and Brumberg, 1980).

However, decreases in food expenditures do not necessarily indicate that quantities consumed vary to the same extent. After retirement, relatively cash-poor but time-rich households might devote more time to shop for bargains or produce time-intensive and relatively cheaper home-cooked meals (Hurst, 2008; Stancanelli and Van Soest, 2012). Empirical evidence for this theory has been presented in Aguiar and Hurst (2005) for the US and in Chen et al. (2017) and Dong and Yang (2017) for China. Yet, recent work by Stephens and Toohey (2018), who expanded upon the influential Aguiar and Hurst (2005) study challenged these results, finding that caloric and nutrient intake falls at retirement in numerous cross-

sectional and longitudinal US data sets.[1] Considering not only expenditures but actual food quantities consumed appears crucial to settle the debate surrounding the retirement food consumption puzzle but this has rarely been done in previous work.

In addition, the aforementioned studies relied on food frequency questionnaires which may be subject to bias. In fact, there is substantial evidence using biomarkers to assess self-reported food intake that individuals under-report caloric and protein intake (Livingstone and Black, 2003). If this behaviour was systematic, that is to say if all individuals under-report consumption in the same way, this would not generate biased results. Yet, this assumption is questionable as many studies found that under-reporting is heterogeneous with respect to certain individual characteristics.[2]

Finally, variations in different food products consumed do not have the same health effects due to differences in nutritional composition. Knowing how diet patterns change is important to assess changes in nutrient intake which in turn is useful to infer potential health effects. Only few studies such as Chen et al. (2017) or Stephens and Toohey (2018) investigate the impact of retirement on the level of different food groups. To the best of our knowledge, no such study exists using European data.

Our objective is to assess the impact of the household head's transition to retirement on food consumption not only in terms of household expenditure but also in terms of actual quantities purchased in order to assess nutrient intake variations. We use detailed home-scan data on all food items purchased by a representative panel of French households from *Kantar Worldpanel* covering the period 2005 to 2014. Together with Stephens and Toohey (2018), this is one of the first studies using longitudinal data to investigate the impact of retirement on household food consumption. Using scanner data instead of survey recall data avoids potential bias from misreporting. The great detail of the data allows us to differentiate several food categories and to control for various household and individual characteristics. We translate the estimated variations in household food quantities purchased into changes in individual nutrient intakes, using the INCA2 dietary intake database (Dubuisson et al., 2010).

As the decision to retire is often a choice and likely to be determined by a range of

[1] Stephens and Toohey (2018) explained the differences between their findings by the fact that methodological changes occurred between the 1989-91 and 1994-96 waves of the Continuing Survey of Food Intake of Individuals (CSFII) which are the waves used by Aguiar and Hurst.

[2] A high BMI or the fact of being weight conscious, for example, appear to be positively associated with under-reporting, whereas old age has been found to be negatively associated (Livingstone and Black, 2003).

unobservable characteristics which may be correlated with food consumption (e.g. health status, time preference), we expect the Ordinary Least Squares estimates to be inconsistent. We exploit the longitudinal aspect of the data and implement a household fixed effect model which allows us to control for *time-invariant* household characteristics. However, our estimates may still be biased if any *time-varying* household characteristics are correlated with retirement status and food consumption. Following the previous literature (see for example Battistin et al. 2009 or Godard 2016), we address this endogeneity issue by using the legal minimum age for retirement as an instrument for retirement status. This identification strategy rests on the fact that reaching the minimum legal age for retirement, and thus becoming eligible to pension benefits, exerts a powerful influence on the individual's decision to retire (Diamond and Gruber, 1999), making retirement increasingly likely around this age. This *discontinuous incentive in retirement schemes* provides an exogenous shock on retirement behaviour which we exploit to estimate the causal impact of transition to retirement on food purchases.

We find that households decrease their total expenditure on food and the amount of food purchased by around 12% to 13% upon retirement. Controlling for time-varying household characteristics through the instrumental variable design yields even stronger decreases of 26% to 29%. Our findings are larger compared to the results from the previous literature which documents that declines in food expenditure following retirement in Western countries range generally from 4% to 14%. Yet, we are not the first paper finding relatively stronger in France. In a comparable study using the 2001 French Consumer Budget Survey, Moreau and Stancanelli (2015) found that retirement leads French households to decrease food expenditure by 18%.

The decline in expenditure appears to be proportional to the decline in quantities purchased. Supposing that households consume what they purchase, this suggests that households are not only spending less money on food but they are also consuming a smaller quantity of food. This is contrary to the hypothesis that retired individuals modify their purchasing behaviour in a way to decrease food expenditure without decreasing their level of actual food intake. We find evidence for larger declines in food purchases in households with lower pre-retirement income, suggesting that the savings and social safety net resources of these households do not allow them to smooth consumption upon retirement. Finally, our results indicate that the decrease in food purchases we find at the aggregate level is driven by a decline in the purchase of food items from animal origins. Consuming less food from animal origins and therefore less fats and protein is likely to undermine retirees' diet balance.

# 2. Data and Method

## *2.1. Data*

We use home-scan data for France from *Kantar Worldpanel*, covering the period 2005 to 2014. The data set provides detailed information on all purchases of food products, including food products without a bar code, for a representative consumer panel of more than 33,188 households.[3] Available information on household and individual characteristics include the number of household members, household income bins, individual socioeconomic categories (SEC), age, sex, height, weight, education level, occupation status, the number of meals taken at home during a typical week, information on potential production of food at home in terms of the presence of a garden or fruit trees and the location of the family home (rural versus urban). Information on food purchases include product type, quantity, price and purchase date.

To investigate the impact of transition to retirement, we focus on a subset of 1,626 households for which we observe the retirement of either the household head or the spouse and for which we have data at least one year before and one year after retirement.[4] To facilitate our analysis, we discard 100 households in which both head and spouse retire but at different points in time. Our results are not sensitive to the inclusion of these households. We are left with 944 households in which we only observe the retirement of the household head, 420 in which we only observe the spouse's transition into retirement and 162 households in which both spouses retire the same year. Our results are not sensitive to the exclusion of the households in which both spouses retire the same year. The earliest age at which we observe retirement for any household head is 43 and for spouses it is 39. See also the distribution of age at retirement in Figure A1 of the Appendix.[5] We omit the year in which we observe the transition to retirement because we don't know the precise date at which the individual exists the work force and therefore cannot distinguish pre- and post-retirement consumption.

The food products are organised into the following 6 groups: food from animal origins

[3]Kantar is a private company specialised in the construction of consumer panels and analysis for market research purposes. The firm provides households with hand-held scanners which are used to scan all purchases of food products with a bar code. Food items without a bar code are entered manually by the panellist.

[4]This choice is motivated in more detail in the next section.

[5]Our results remain qualitatively the same when we restrict the sample to households in which individuals are aged 50 to 70 years.

which includes red meat (beef and veal), other meat (poultry, pork, lamb, etc.), cooked meat (ham, pâté, sausages, bacon, etc.), dairy (milk, cheese, butter, cream, etc.), fish and seafood; food from plant origins which includes potatoes, grain products (bread, pasta, rice, wheat flour and cereals), fruits (including juices) and vegetables (including soups); unhealthy food items which comprises ready meals (pizza, sauerkraut, cassoulet, etc.), salt-fat products (finger food, chips, crackers, appetisers) and sugar-fat products (candy, chocolate, cookies, pastry, ice cream, jam, etc.); oils and condiments; soft drinks; and alcohol. Defining these food groups is useful to alleviate the estimation process while still allowing us to investigate how diet patterns evolve around retirement. As the nutritional composition of the food items differs across the food groups, relative changes in the amount purchased of these groups imply different changes in nutrient intake. Knowing how nutrient intakes vary is useful to infer potential health effects. This allows us for example to investigate whether individuals change their consumption of food from animal products such as has been found by Chen et al. (2017). Table A1 in the Appendix provides descriptive statistics.

### *2.2. Method*

We investigate the impact of the household head's transition to retirement on annual household food purchases, both in terms of total expenditures denominated in Euro and total quantities measured in grams. Simple ordinary least square (OLS) regressions are likely to yield biased estimates as certain unobserved household characteristics may affect both food consumption and retirement status. In theory, the direction of the bias is not clear. Health issues may force individuals to retire earlier than expected, leading to a sharp permanent decline in their lifetime resources which should cause a decrease in consumption. This decline in food consumption could then wrongly be interpreted as caused by retirement when the actual underlying reason is a deterioration of health. A positive shock to wealth (e.g the end of a mortgage payment, inheritance) could lead to increased household consumption as well as anticipated retirement which we could wrongly interpret as a positive effect of retirement on food consumption. We expect rational households to choose the moment of retirement which allows them to optimise their consumption. However, this decision depends on unobservable time preferences which may also be correlated with household wealth and food consumption.

We control for time-invariant unobserved household characteristics by considering the

following household fixed effects (FE) model

$$C_{ht} = \alpha + \beta R_{ht} + \alpha_h + \delta_t + \rho X_{ht} + \epsilon_{ht},$$

where $C_{ht}$ denotes the different measures of food consumption of household $h$ at time $t$, $R_{ht}$ is equal to 1 when the household head of household $h$ is retired at time $t$ and 0 otherwise, $\alpha_h$ are household fixed effects and $\delta_t$ are year fixed effects. We denote $X_{ht}$ a vector of time-varying household characteristics, including family size, family caloric needs[6], the average number of meals taken at home in a typical week to control for the amount of food eaten at home relative to food eaten outside the home, a dummy variable indicating whether the household possesses a garden or fruit trees, and a dummy indicating whether households live in a rural area to account for the possibility that they may produce food at home. We control linearly for the age of the retiring individual.[7] The parameter of interest is $\beta$, the difference between household food purchases before and after the retirement of the household head. We run the regressions on the logarithm of the annual household food purchases. Standard errors are adjusted for clustering at the level of the household.[8]

Household FE allow us to control for time-invariant unobservable characteristics. However, $\hat{\beta}$ is still biased if some time-varying unobserved household characteristics are correlated with retirement status. This may be the case if the individual faces a sudden shock to health (onset of an illness) or a sudden shock to wealth (e.g the end of a mortgage payment, inheritance). To address this issue, we estimate a Fixed Effects Instrumental Variable (FEIV) model in which we use the French legal minimum age for retirement as an instrument for retirement status. This kind of instrumental variable has been used several times (see for example Battistin et al. (2009), Li et al. (2015) or Godard (2016)). When individuals reach the legal minimum age for retirement, they become eligible to either reduced or full pension benefits, conditional on a sufficient number of years of social security contributions. This age is situated between 60 to 62 years depending on the individual's year of birth.[9]

The legal minimum retirement age is a good instrument. First, it has been shown to exert a powerful influence on individuals' retirement behavior (Diamond and Gruber, 1999; Godard, 2016). It is also confirmed in our data where we can see from Figure A1 in the Appendix that most individuals retire between the age 60 to 62. Second, reaching the legal

[6]Constructed as the sum of the Basal Metabolic Rate (BMR) of each family member using their height, weight, age and gender.

[7]Controlling more flexibly for age by using polynomial terms in age leads to qualitatively similar results.

[8]See Abadie et al. (2017) for the relevance of adjusted standard errors for clustering.

[9]See the *"Décret n° 2012-847 du 2 juillet 2012 relatif à l'âge d'ouverture du droit à pension de vieillesse"*, `https://www.legifrance.gouv.fr/eli/decret/2012/7/2/AFSS1227748D/jo/texte`

minimum retirement age cut-off, after controlling for age, is unlikely to be correlated with food consumption behavior, except through the increased probability of retiring. Formally, the retirement decision of the household head in household $h$ at time $t$, $R_{ht}$ is instrumented by an indicator variable, $A_{ht}$, equal to 1 if the household head's age is above the minimum retirement age and equal to 0 otherwise.

The estimates are obtained from a two-stages least squares estimation with the following first-stage equation

$$R_{ht} = \alpha_0 + \beta_0 A_{ht} + \alpha_h + \delta_t + \rho_0 X_{ht} + \epsilon_{0,ht}$$

and second-stage equation

$$C_{ht} = \alpha + \beta \hat{R}_{ht} + \alpha_h + \delta_t + \rho X_{ht} + \epsilon_{ht}.$$

All other variables correspond to what has been presented in the FE model. This model allows us to control for both time-invariant and time-varying omitted variables. The FEIV regressions yield estimates of a Local Average Treatment Effect (LATE) which is identified for compliers, meaning the subset of individuals whose behavior is shifted by the instrument. More precisely, compliers are individuals who reached the legal minimum age and retired but would not have done so had they not reached this minimum age, and individuals whose eligibility to pension did not change and did not retire but would have retired had they reached the legal minimum retirement age.

Employing household FE means that we exploit within-household variation in food consumption. The parameter $\beta$ is not identified for households in which the household head does not change retirement status over time. The estimation method selected explains why we focus on the subset of the 1,626 households for which we observe the retirement of either the household head or the spouse and for which we have data at least one year before and after retirement.[10]

[10]Using this subset of households does not bias our estimates. The potential endogeneity bias due to the fact that individuals decide when to retire affects the entire population, including households observed at moments other than transition to retirement. We address this endogeneity issue by implementing the instrumental variable approach as mentioned above.

# 3. Results

## *3.1. The impact of retirement on aggregate household food purchases*

Tables 1 and 2 present results concerning the impact of the household head's retirement on aggregate household food quantities purchased and food expenditure. The estimates from the FE regressions suggest that retirement is associated with a 12% to 12.9% decrease in total quantities purchased and a 13.7% to 14.5% decrease in total food expenditures. When we control for time-varying unobserved household characteristics in the FEIV model, our estimates are over 10 percentage points larger. Food quantities purchased and expenditure drop in between 26% and 29%.

Results are robust to the inclusion of the full range of observable household characteristics. The coefficient on the number of household members becomes statistically insignificant once we include the household total calorie needs. This is not surprising as those two variables are highly correlated and household calorie needs is likely to be the better measure as it accounts for sex, age, weight and height. Both of our proxies for the household's home production potential - the variable indicating whether the household possesses a garden or fruit trees and the indicator equal to one if the household lives in a rural area - are not statistically significant. Their inclusion or exclusion do not modify our results.[11] The first-stage F-statistics of the test on the excluded instruments reported at the bottom of the Tables 1 and 2 suggest that we can reject the hypothesis of weak instrument as these statistics exceed by far the rule-of-thumb value of 10 proposed by Stock and Yogo (2002). Table A2 in the Appendix presents the first-stage regression results.

The effects we find in our data are large compared to what has been documented in previous research. In Western countries, declines in food expenditure following retirement have been shown to range from 4% (Aguila et al., 2011) to 14% (Hurst, 2006; Hurd and Rohwedder, 2003; Hurst, 2008; Li et al., 2015). Few comparable results exist concerning the effects in France. To the best of our knowledge, the only study comparable to ours and using French data is Moreau and Stancanelli (2015) who reported a 18% drop of household food expenditure following retirement. Both the findings of Moreau and Stancanelli (2015) and our estimates suggest that the effect of retirement on food consumption in France may

[11] We also tried out specifications in which we include a control for the spouse's employment status. We observe changes in employment status in only 38 of the households and including this control does not affect the results.

Table 1: Effect of the household head's retirement on food quantities purchased

| | FE | | FEIV | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 1 | Model 2 |
| Retired | -0.129*** | -0.120*** | -0.265* | -0.290** |
| | (0.025) | (0.025) | (0.139) | (0.137) |
| Age household head | 0.006*** | 0.006*** | 0.007*** | 0.007*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Household members | 0.133*** | -0.008 | 0.133*** | -0.012 |
| | (0.017) | (0.042) | (0.017) | (0.041) |
| Household BMR | | 8.7e-05*** | | 9.0e-05*** |
| | | (0.000) | | (0.000) |
| Nb. meals | | 0.050*** | | 0.049*** |
| | | (0.010) | | (0.011) |
| Garden, fruit trees | | -0.039 | | -0.037 |
| | | (0.034) | | (0.033) |
| Rural household | | -0.036 | | -0.034 |
| | | (0.084) | | (0.083) |
| Constant | 12.72*** | 12.70*** | | |
| | (0.126) | (0.131) | | |
| Observations | 7756 | 7248 | 7756 | 7248 |
| Year dummies | Yes | Yes | Yes | Yes |
| First-stage F-stat | | | 116.2 | 107.7 |

Note: The columns FE (FEIV) stand for Fixed Effects (Fixed Effects Instrumental Variable) estimation method. Robust standard errors clustered at the household level are in parenthesis.
* p<0.10, ** p<0.05, *** p<0.01

Table 2: Effect of the household head's retirement on food expenditure

| | FE | | FEIV | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 1 | Model 2 |
| Retired | -0.145*** | -0.137*** | -0.240* | -0.293** |
| | (0.025) | (0.025) | (0.139) | (0.137) |
| Age household head | 0.005*** | 0.005*** | 0.006*** | 0.007*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Household members | 0.111*** | -0.016 | 0.111*** | -0.020 |
| | (0.017) | (0.042) | (0.017) | (0.042) |
| Household BMR | | 7.7e-05*** | | 8.0e-05*** |
| | | (0.000) | | (0.000) |
| Nb. meals | | 0.045*** | | 0.045*** |
| | | (0.010) | | (0.010) |
| Garden, fruit trees | | -0.021 | | -0.020 |
| | | (0.032) | | (0.032) |
| Rural household | | 0.001 | | 0.003 |
| | | (0.084) | | (0.083) |
| Constant | 7.088*** | 7.069*** | | |
| | (0.122) | (0.130) | | |
| Observations | 7756 | 7248 | 7756 | 7248 |
| Year dummies | Yes | Yes | Yes | Yes |
| First-stage F-stat | | | 116.2 | 107.7 |

Note: The columns FE (FEIV) stand for Fixed Effects (Fixed Effects Instrumental Variable) estimation method. Robust standard errors clustered at the household level are in parenthesis.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

be stronger than in other countries. As a potential explanation, Moreau and Stancanelli (2015) remarked that the earnings distribution in France is more compressed than in other countries (OECD, 2008) and that French households may on average spend more money on food compared to their counterparts in the USA.

We find that the coefficients on expenditure and quantities purchased are of a similar magnitude. This suggests that households are not only spending less money on food, but they also buy a smaller amount of food. Supposing that households consume what they buy, this would mean that retirement leads households to decrease their food consumption. This runs counter to the results of most notably Aguiar and Hurst (2005) who find that although food expenditure decreases at retirement, actual food intake does not fall at retirement. It is in line, however, with recent findings by Stephens and Toohey (2018) who expanded upon the Aguiar and Hurst analysis and found also that food consumption falls at retirement.[12]

The FE model yields coefficients of a smaller magnitude compared to the coefficients from the FEIV model. Not accounting for time-varying household characteristics through the instrumental variable approach apparently leads us to underestimate the effects of retirement on food purchases. Similarly, previous work has shown OLS estimates to be downward biased compared to instrumental variable estimates (see for example Fisher et al. (2008)). This downward bias of the FE estimates may for example be due to unobserved positive shocks to the individual's wealth. Negative shocks to health can be ruled out as a predominant source of bias because such shocks would have biased the FE estimates upwards (see the discussion on the direction of the endogeneity bias in the method section). This is in accordance with evidence from previous studies which found that health problems account for a small proportion of individuals' retirement decision (French, 2005).

We briefly investigated the effect of the spouse's retirement on household food consumption and report the results in Tables A3 and A4 in the Appendix. We find that the spouse's retirement affects household food consumption in a similar way than the retirement of the household head in the FE model. The estimates from the FEIV regressions, however, are no longer statistically significant, probably due to the smaller sample size.

[12] Stephens and Toohey (2018) explained the differences between the findings by the fact that methodological changes occurred between the 1989-91 and 1994-96 waves of the Continuing Survey of Food Intake of Individuals which are the waves used by Aguiar and Hurst.

### *3.2. Heterogeneous effects with respect to household income and effects at the food group level*

We divide households into quintiles according to household income per capita averaged over the years prior to the household head's retirement. We regress food expenditures and quantities purchased on the interaction terms of the retirement status with the indicator variables for the income quintile.[13] Table 3 shows the results from FE and the FEIV regressions. The first-stage regression results of the FEIV are reported in Table A5 in the Appendix.

Food consumption appears to be more affected in households belonging to the lower pre-retirement income quantiles. Households from the lowest quintile reduce quantities purchased by 16.4%, whereas quantities purchased drop by 10.7% in the fourth quintile. The coefficient in the last quintile is more than halved at 6.5% and the effect is only statistically significant at the 10% level. The pattern is similar concerning food expenditure. It also appears in the estimates from the FEIV, albeit less pronounced. Finding larger declines in consumption upon retirement among low income households suggests that their savings and social safety net resources do not allow these households to smooth food consumption upon retirement. However, the differences between the coefficients on the different quintile groups are not statistically significant.

Heterogeneous effects across the wealth or income distribution have rarely been investigated in the literature. The existing evidence is in line with our results. Bernheim et al. (2001) found that the percentage drop in food expenditure was larger for households with lower wealth and lower income replacement rates. Results from Aguiar and Hurst (2005) suggest that while the average household did not experience any decline, households with very little accumulated wealth did experience some decline in actual food intake associated with retirement. Hurd and Rohwedder (2003) found that the declines in expenditure at the time of retirement increased as net worth declined.[14]

We finally explore the impact of retirement on diet patterns by estimating separate regressions for each of the 6 food groups. The results are reported in Table 4. The FE model estimates suggest that households decrease their consumption of food from animal origins,

[13]The income brackets are as follows: up to 793 € included, 793 € to 1050 € included, 1050 € to 1379 € included, 1379 € to 1700 € included and over 1700 €.

[14]In a different kind of exercise, Aguila et al. (2011) and Fisher and Marchand (2014) investigated heterogeneous effects across the consumption distribution and find on the contrary evidence for a progressive distributional effects of retirement.

Table 3: Heterogeneous effects of the household head's retirement on food consumption by pre-retirement average per capita household income quintile

| | FE | | FEIV | |
|---|---|---|---|---|
| | Quantities | Expenditure | Quantities | Expenditure |
| Retired, 0-20th perc. | -0.164*** | -0.171*** | -0.327** | -0.326** |
| | (0.039) | (0.039) | (0.142) | (0.143) |
| Retired, 20-40th perc. | -0.129*** | -0.143*** | -0.251* | -0.274* |
| | (0.039) | (0.037) | (0.145) | (0.143) |
| Retired, 40-60th perc. | -0.133*** | -0.146*** | -0.273* | -0.275* |
| | (0.039) | (0.040) | (0.144) | (0.145) |
| Retired, 60-80th perc. | -0.107*** | -0.133*** | -0.288* | -0.294* |
| | (0.040) | (0.039) | (0.154) | (0.152) |
| Retired, 80- 100th perc. | -0.065* | -0.091** | -0.274* | -0.259* |
| | (0.039) | (0.040) | (0.150) | (0.148) |
| Constant | 12.72*** | 7.084*** | | |
| | (0.131) | (0.130) | | |
| Observations | 7248 | 7248 | 7248 | 7248 |
| Year dummies | Yes | Yes | Yes | Yes |

Note: The model includes all covariates: Family size, family caloric needs, the average number of meals taken at home in a typical week to control for the proportion of food eaten at home to food eaten outside the home, a dummy variable indicating whether the household possesses a garden or fruit trees, and a dummy for household living in a rural area to account for the possibility that households may produce food at home. The columns FE (FEIV) stand for Fixed Effects (Fixed Effects Instrumental Variable) estimation method. Robust standard errors clustered at the household level are in parenthesis.
* p<0.10, ** p<0.05, *** p<0.01

food from plant origins and unhealthy food items by around 10% to 12%. Expenditures drop in between 13% and almost 14%. Oils and condiments and soft drinks appear to decrease as well, but less strongly. Concerning alcohol consumption, only the decline in expenditure is statistically significant. The FEIV model only yields statistically significant results for the consumption of products from animal origins which drop by 30% in terms of quantities purchased and by 31% in terms of expenditures. Expenditure on unhealthy foods appears to decrease by 28.4% whereas the change in quantities is not statistically significant.

Table 4: Effect of the household head's retirement at the food category level

| | Animal origins | Plant origins | Unhealthy food | Oils, condiments | Soft drinks | Alcohol |
|---|---|---|---|---|---|---|
| *Effects of retirement on food quantities purchased, FE model* | | | | | | |
| Retired | -0.109*** | -0.117*** | -0.103*** | -0.084*** | -0.096** | -0.054 |
| | (0.034) | (0.030) | (0.027) | (0.028) | (0.048) | (0.042) |
| *Effects of retirement on food quantities purchased, FEIV model* | | | | | | |
| Retired | -0.300** | -0.177 | -0.187 | -0.042 | 0.027 | -0.031 |
| | (0.144) | (0.176) | (0.158) | (0.163) | (0.290) | (0.260) |
| *Effects of retirement on food expenditure, FE model* | | | | | | |
| Retired | -0.134*** | -0.138*** | -0.132*** | -0.072** | -0.117*** | -0.085* |
| | (0.027) | (0.029) | (0.026) | (0.029) | (0.044) | (0.045) |
| *Effects of retirement on food expenditure, FEIV model* | | | | | | |
| Retired | -0.310** | -0.220 | -0.284* | -0.0177 | -0.095 | 0.124 |
| | (0.153) | (0.168) | (0.158) | (0.174) | (0.262) | (0.271) |

Note: The model includes all covariates: Family size, family caloric needs, the average number of meals taken at home in a typical week to control for the amount of food eaten at home relative to food eaten outside the home, a dummy variable indicating whether the household possesses a garden or fruit trees, and a dummy for household living in a rural area to account for the possibility that households may produce food at home. The abbreviation FE (FEIV) stand for Fixed Effects (Fixed Effects Instrumental Variable) estimation method. Robust standard errors clustered at the household level are in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Our results suggest that the decrease we find in total food expenditure and quantities purchased is mainly driven by the decline in purchases of food from animal origins. This is comparable to Chen et al. (2017) who also found that retirement changes diet patterns as individuals consume less food with animal origins.[15]

[15] Even though the estimates from the FEIV are not statistically significant for most food categories, we find that the coefficients on food from plant origins and unhealthy foods are still negative and of a larger

### 3.3. *Nutrient intake variations*

We follow Irz et al. (2015) to translate the variations in household food quantities purchased into changes in food and nutrient intakes at the level of the individual. Assuming that (i) the percentage changes in food consumption are the same for all the members of a given household, (ii) the percentage changes are the same for at-home and out-of-home consumption and (iii) the households consume what they purchase, we apply the statistically significant percentage variations for food products from animal origins obtained in the previous section to average dietary intakes as calculated using the INCA2 database[16]. These variations in INCA2 food items are then translated into variations in nutrient intakes, using the INCA2 matrix of the nutritional contents of the INCA2 food items.

Table 5 reports the changes in nutrient intakes for the lowest and highest (pre-retirement) quintile income group. Results for the other percentile income groups can be obtained from the authors upon request. We find that the intakes of all macro- and micro-nutrients fall upon retirement. The potential health effects of these changes are ambiguous. On the one hand, the large drops in essential nutrients such as protein, calcium and several vitamins are likely to have negative impacts on health, as reflected by the drop of the Mean Adequacy Ratio reported at the bottom of the Table 5.[17] On the other hand, the reduced intake of saturated fatty acids and salt may have positive health benefits. This is summarized in the decrease of the Mean Excess Ratio,[18] which is also reported at the bottom of Table 5.[19]

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magnitude relative to the same estimates from the FE model. We think it is possible that the absence of statistically significant results for these categories in the FEIV is due to loss of precision as standard errors are larger in IV regressions.

[16] *Étude Individuelle des Consommations Alimentaires 2* de 2006-2007, (Agence Française de Sécurité Sanitaire des Aliments, 2009) which documents the individual food consumption of French adult consumers (Dubuisson et al., 2010).

[17] This is an index comparing the individual's intake of 20 essential nutrients compared to the Recommended Dietary Allowance (RDA). It is calculated as $MAR = \frac{1}{20} \cdot \sum_{bn=1}^{20} \frac{intake_{bn}}{RDAbn} \cdot 100$. See Madden et al. (1976).

[18] It is an indicator for consumption of nutrients to be limited. A decline in this index therefore is good for health. It is calculated as $MER = \left[\frac{1}{3} \cdot \left(\sum_{hn=1}^{a} \frac{intake_{hn}}{MRVhn} \cdot 100\right)\right] - 100$. See Vieux et al. (2013).

[19] As an additional exercise, we fed the variations in nutrient intake into the DIETRON epidemiological model (Scarborough et al., 2012) to estimate changes in mortality rates attributable to coronary heart diseases, strokes and cancers. We find that the diet changes may translate into 4,363 deaths avoided per year. However, DIETRON considers only changes in energy, fruit, vegetables, fibres, total fat, mono-unsaturated fatty acids, polyunsaturated fatty acids, saturated fatty acids, dietary cholesterol and salt. Changes which have potentially important negative health effects, such as the fall in protein, calcium, vitamins, etc. are not considered in the model.

Table 5: Changes in the nutritional profile of the diet in terms of % variation in nutritional intakes and overall nutritional indicators for the lowest and highest (pre-retirement) quintile income group

| | Males by income percentile | | Females by income percentile | |
|---|---|---|---|---|
| Nutritional indicator | 0-20 perc. | 80-100 perc. | 0-20 perc. | 80-100 perc. |
| Proteins | -20.91 | -17.69 | -20.52 | -17.47 |
| Fibres | -0.30 | -0.20 | -0.32 | -0.30 |
| Magnesium | -8.65 | -8.04 | -9.47 | -8.04 |
| Potassium | -9.21 | -7.85 | -9.58 | -8.26 |
| Calcium | -16.75 | -14.45 | -17.05 | -15.08 |
| Iron | -10.02 | -9.33 | -10.34 | -7.74 |
| Copper | -9.79 | -8.29 | -8.78 | -8.47 |
| Zinc | -19.62 | -16.90 | -19.03 | -16.36 |
| Selenium | -21.11 | -18.49 | -20.44 | -16.99 |
| Iodine | -16.95 | -13.30 | -18.77 | -15.12 |
| Vitamin A | -13.35 | -10.85 | -11.52 | -9.46 |
| Vitamin B1 | -12.40 | -10.34 | -11.72 | -9.52 |
| Vitamin B2 | -17.33 | -14.83 | -17.07 | -14.61 |
| Vitamin B3 | -18.52 | -16.03 | -18.01 | -15.12 |
| Vitamin B6 | -12.73 | -11.16 | -12.42 | -10.35 |
| Vitamin B9 | -7.36 | -6.07 | -6.64 | -5.74 |
| Vitamin B12 | -27.45 | -23.10 | -26.79 | -23.50 |
| Vitamin C | -1.44 | -1.15 | -1.19 | -1.09 |
| Vitamin D | -0.56 | -0.71 | -0.79 | -0.61 |
| Vitamin E | -3.96 | -3.88 | -3.98 | -3.25 |
| Saturated fatty acids | -17.67 | -15.26 | -16.61 | -13.88 |
| Salt | -12.00 | -9.46 | -9.92 | -8.38 |
| Free Sugar | -1.43 | -0.80 | -1.92 | -2.03 |
| Mean Adequacy Ratio | -7.21 | -7.55 | -8.02 | -5.98 |
| Mean Excess Ratio | -119.53 | -89.67 | -23.91 | -18.70 |
| Energy density | -3.45 | -2.99 | -2.49 | -2.01 |

Note: The columns 0-20 perc. (80-100 perc.) stand for first (last) quintile income group. The Mean Adequacy Ratio is an overall nutritional intake adequacy for 20 essential nutrients (first 20 entries of the table up to Vitamin A) based on the individual's diet compared to the Recommended Dietary Allowance. The Mean excess ratio is the average percentage of the Maximum Recommended Value for saturated fatty acids, salt and free sugar to be limited. The Energy density is defined as kilo calorie intake per 100 gram of diet.

# 4. Discussion and policy implications

We find that households decrease the amount of food they purchase after the household head's transition to retirement. We believe that this decline in food purchases for consumption at home is not compensated by in increase in food eaten away from home. Although we do not have information on food eaten away from home, we control for the potential compensation effect by including the average number of meals taken at home in a typical week. In addition, the existing evidence suggests that individuals spend less on food eaten away from home after retirement (Bernheim et al., 2001; Miniaci et al., 2003; Hurd and Rohwedder, 2006; Fisher et al., 2008; Hurst, 2008; Battistin et al., 2009; Chen et al., 2017; Dong and Yang, 2017).

It is possible that individuals substitute market goods with home produced goods which could lead to the observed decrease in household food quantities purchased although actual food quantities consumed do not vary. We control for the potential household's home production by including information on whether the household lives in a rural area or possesses a garden and fruit trees, but we acknowledge the limitations of this approach. Ideally, we would also like to control for changes in time use (e.g. time spend gardening or cooking) or for changes in the amount of food waste generated by the household. Not having such information is a caveat of our study. Still, it seems unlikely that households can produce a big enough amount of food to compensate the 29% drop in food quantities purchased in the market. This appears particularly unlikely when it comes to compensating the 30% decline in purchases of food from animal origins. We therefore assume in our policy recommendations that the drop in household food quantities purchased translates, at least partially, into decreased household food consumption.

We believe that household's maximising behaviour does not account for a significant part of the observed drop in food consumption. Individuals may have reduced calorie needs as they stop work-related activities or they may suffer from a feeble appetite due to certain psychological changes and therefore rationally chose to consume less food. However, declines in calorie needs are likely to be important only for a minority of individuals who worked in the most physically strenuous jobs, whereas many individuals who retire from sedentary jobs may, on the contrary, increase their calorie needs by engaging in more sport-related activities. The impact of psychological changes is also potentially ambiguous. Mental health problems are unlikely to systematically reduce appetite as they may also induce overeating (see for example Kivimäki et al. (2006); Privitera et al. (2013)). In addition, the individuals most affected by psychological changes are likely to be those who retire due to sickness or who have been retired for a long period of time. We control for potential endogeneity from retirement due to health problems and we look at the short-term effects of transitioning to retirement. We find evidence for stronger decreases in food purchases among households at the lower end of the (pre-retirement) income distribution, suggesting that the household's savings or safety net resources do not allow them to smooth their consumption upon retirement. This indicates welfare losses that may be addressed through suitable policy intervention.

We expect that the changes in diet patterns (notably the decreased consumption of food from animal origins) lead to reduced intake of saturated fatty acids and salt which may have positive impacts on health, but also to reduced intake of micro-nutrients beneficial to health such as protein, calcium and vitamins. Although energy needs decrease with age, the need for most nutrients remains relatively unchanged. Malnutrition in older age interacts with the underlying age-related changes, often taking the form of reduced muscle and bone mass and increases the risk of frailty. Malnutrition has also been associated with diminished cognitive function, a diminished ability to care for oneself, and a higher risk of becoming care dependent (World Health Organization, 2015). Addressing elderly malnutrition would result in potentially important gains in terms of reduced suffering and reduced costs to health care systems.

We therefore recommend policy makers to assure that retirees have the financial means to maintain a suitable diet, for example by providing supplementary income through food stamps. In France, food vouchers or "chèques alimentaires" do exist. The vouchers are attributed conditional on social criteria via Communal Social Action Centres ("Centre communal d'action sociale"). However, the service is not targeted to the elderly and information about service provision is not spread systematically. The allocation of food vouchers could be generalised or at least it could be ensured that individuals are informed about the food aid available to them.

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Table A1: Household and individual characteristics, and household purchases

**Household and individual characteristics**

| **Variable** | **Mean** | **Std. Dev.** | **Min.** | **Max.** | **N** |
|---|---|---|---|---|---|
| Number of household members | 2.12 | 0.91 | 1 | 8 | 12947 |
| Age of the household head | 62.25 | 7.27 | 18 | 91 | 12947 |
| Age of the spouse | 60.33 | 7.07 | 15 | 95 | 12947 |
| Total household BMR | 3037.95 | 1397.03 | 995.30 | 11402.2 | 12327 |
| Number of meals taken at home | 2.06 | 0.87 | 0 | 14.79 | 12826 |
| Home production capacity = 1 | 0.58 | 0.49 | 0 | 1 | 12947 |
| Lives in rural area = 1 | 0.19 | 0.39 | 0 | 1 | 12947 |
| Pre-retirement per capita income | 1338.61 | 710.4 | 216.67 | 5000 | 12947 |

**Annual household purchases by food category**

| **Variable** | **Mean** | **Std. Dev.** | **Min.** | **Max.** | **N** |
|---|---|---|---|---|---|
| *Annual quantity (grams)* | | | | | |
| Products from animal origins | 272365.01 | 159860.31 | 0 | 1335978.75 | 12947 |
| Products from plant origins | 282769.55 | 192511.83 | 0 | 6602271 | 12947 |
| Unhealthy food products | 74062.69 | 52086.28 | 0 | 535376 | 12947 |
| Oil, condiments | 23809.71 | 16116.42 | 75 | 200486 | 12904 |
| Soft drinks | 53665.99 | 88968.33 | 130 | 1164000 | 12169 |
| Alcoholic beverages | 85149.23 | 108465.66 | 25 | 1182750 | 12634 |
| *Annual expenditure (Euro)* | | | | | |
| Products from animal origins | 1442.51 | 893.61 | 0 | 6910.97 | 12947 |
| Products from plant origins | 588.68 | 376.11 | 0 | 3628.59 | 12947 |
| Unhealthy food products | 530.88 | 359.15 | 0 | 4015.83 | 12947 |
| Oil, condiments | 88.71 | 59.05 | 0.43 | 1160.64 | 12904 |
| Soft drinks | 58.42 | 76.04 | 0.18 | 914.06 | 12169 |
| Alcoholic beverages | 375.9 | 438.16 | 0.42 | 4443.16 | 12634 |

Note: The age range for the household head and the spouse is large because there sometimes exists a large difference in age between the retiring and the non-retiring individual. It is stated in the data description as provided by Kantar Worldpanel that the household head and the second individual (the "panellist" or the person who registers the purchases) are normally a male-female couple. However, we noted that there are some cases where a much younger individual (perhaps an adult child) is referenced as household head (the spouse) whereas the much older spouse (household head) retires.

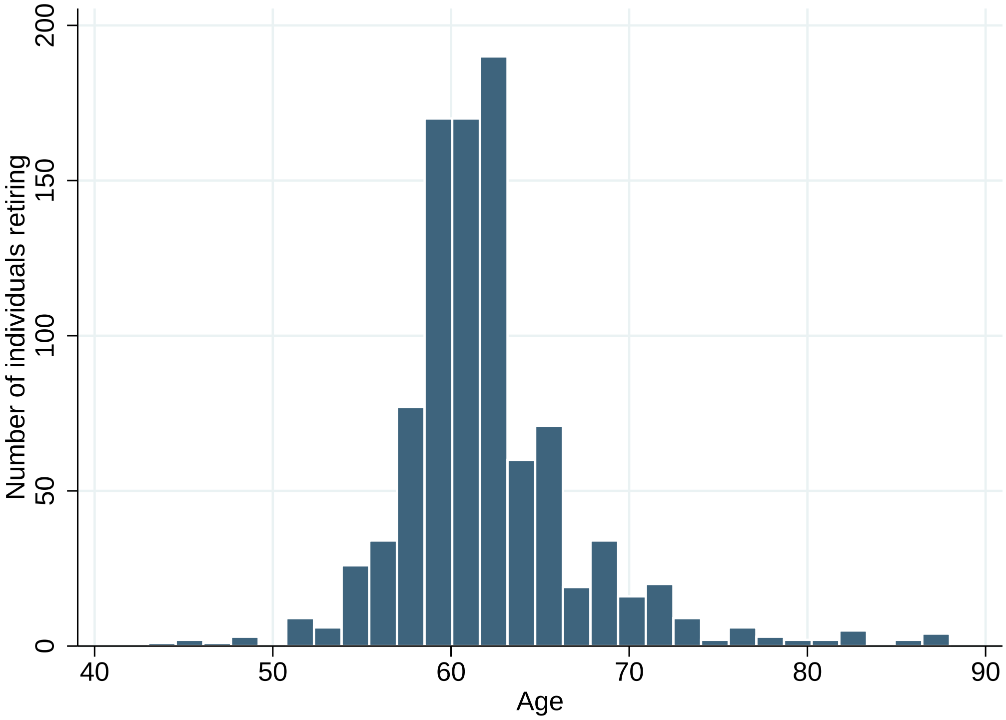


Figure A1.Number of individuals retiring by age

Table A2: First stage results - Retirement of the household head

| | Model 1 | Model 2 |
|---|---|---|
| Reached legal minimum retirement age | 0.153*** | 0.153*** |
| | (0.014) | (0.015) |
| Age household head | 0.005*** | 0.005*** |
| | (0.001) | (0.001) |
| Household members | 3.4e-04 | -0.022 |
| | (0.010) | (0.026) |
| Household BMR | | 1.7e-05 |
| | | (0.000) |
| Nb. meals | | -0.006 |
| | | (0.007) |
| Garden, fruit trees | | 9.7e-04 |
| | | (0.019) |
| Rural household | | 0.011 |
| | | (0.042) |
| Constant | -0.373*** | -0.357*** |
| | (0.064) | (0.071) |
| Observations | 7756 | 7248 |
| $R^2$ | 0.727 | 0.725 |
| Year dummies | Yes | Yes |
| F-stat | 116.2 | 107.7 |

Note: Robust standard errors clustered at the household level are in parenthesis.
* p<0.10, ** p<0.05, *** p<0.01

Table A3: Effect of the spouse's retirement on food quantities purchased

| | FE | | FEIV | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 1 | Model 2 |
| Retired | -0.165*** | -0.159*** | 0.164 | 0.151 |
| | (0.030) | (0.031) | (0.192) | (0.191) |
| Age spouse | -0.004 | -0.005 | -0.005 | -0.006 |
| | (0.004) | (0.004) | (0.005) | (0.005) |
| Household members | 0.136*** | -0.041 | 0.142*** | -0.042 |
| | (0.031) | (0.046) | (0.032) | (0.047) |
| Household BMR | | 1.1e-04*** | | 1.2e-04*** |
| | | (0.000) | | (0.000) |
| Nb. meals | | 0.031** | | 0.035** |
| | | (0.016) | | (0.016) |
| Garden, fruit trees | | -2.5e-04 | | 0.001 |
| | | (0.048) | | (0.049) |
| Rural household | | 0.108 | | 0.076 |
| | | (0.102) | | (0.113) |
| Constant | 13.43*** | 13.42*** | | |
| | (0.260) | (0.273) | | |
| Observations | 3932 | 3752 | 3932 | 3752 |
| Year dummies | Yes | Yes | Yes | Yes |
| First-stage F-stat | | | 51.11 | 50.24 |

Note: The columns FE (FEIV) stand for Fixed Effects (Fixed Effects Instrumental Variable) estimation method. Robust standard errors clustered at the household level are in parenthesis.
* p<0.10, ** p<0.05, *** p<0.01

Table A4: Effect of the spouse's retirement on food expenditure

| | FE | | FEIV | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 1 | Model 2 |
| Retired | -0.175*** | -0.166*** | 0.047 | 0.033 |
| | (0.030) | (0.031) | (0.190) | (0.191) |
| Age spouse | -0.007 | -0.007 | -0.008 | -0.008 |
| | (0.005) | (0.006) | (0.006) | (0.006) |
| Household members | 0.110*** | -0.079 | 0.114*** | -0.079 |
| | (0.033) | (0.054) | (0.034) | (0.055) |
| Household BMR | | 1.2e-04*** | | 1.2e-04*** |
| | | (0.000) | | (0.000) |
| Nb. meals | | 0.041*** | | 0.043*** |
| | | (0.015) | | (0.015) |
| Garden, fruit trees | | 0.011 | | 0.012 |
| | | (0.044) | | (0.045) |
| Rural household | | 0.104 | | 0.083 |
| | | (0.121) | | (0.127) |
| Constant | 7.956*** | 7.924*** | | |
| | (0.320) | (0.338) | | |
| Observations | 3932 | 3752 | 3932 | 3752 |
| Year dummies | Yes | Yes | Yes | Yes |
| First-stage F-stat | | | 51.11 | 50.24 |

Note: The columns FE (FEIV) stand for Fixed Effects (Fixed Effects Instrumental Variable) estimation method. Robust standard errors clustered at the household level are in parenthesis.
* p<0.10, ** p<0.05, *** p<0.01

Table A5: First stage results - Effect of retirement on food quantities purchased, heterogeneous effects by pre-retirement household quintile income per capita group

| | Pre-retirement household quintile income group | | | | |
|---|---|---|---|---|---|
| | 0-20th perc. | 20-40th perc. | 40-60th perc. | 60-80th perc. | 80-100th perc. |
| Reached legal min. retirement age | | | | | |
| 0-20th perc. | 0.626*** | -0.108*** | -0.0988*** | -0.110*** | -0.116*** |
| | (0.028) | (0.011) | (0.010) | (0.010) | (0.011) |
| 20-40th perc. | -0.116*** | 0.639*** | -0.105*** | -0.122*** | -0.131*** |
| | (0.012) | (0.030) | (0.010) | (0.011) | (0.011) |
| 40-60th perc. | -0.121*** | -0.119*** | 0.645*** | -0.123*** | -0.135*** |
| | (0.012) | (0.011) | (0.027) | (0.011) | (0.012) |
| 60-80th perc. | -0.112*** | -0.112*** | -0.102*** | 0.584*** | -0.130*** |
| | (0.011) | (0.011) | (0.010) | (0.029) | (0.011) |
| 80- 100th perc. | -0.109*** | -0.112*** | -0.103*** | -0.120*** | 0.574*** |
| | (0.011) | (0.011) | (0.010) | (0.011) | (0.026) |
| Constant | 0.229** | 0.00367 | -0.117** | -0.239*** | -0.228*** |
| | (0.106) | (0.091) | (0.051) | (0.043) | (0.062) |
| Observations | 7248 | 7248 | 7248 | 7248 | 7248 |
| $R^2$ | 0.464 | 0.431 | 0.432 | 0.389 | 0.412 |
| F-stat | 278.85 | 223.93 | 276.73 | 201.53 | 251.08 |

Note: Robust standard errors clustered at the household level are in parenthesis.
* p<0.10, ** p<0.05, *** p<0.01
The reported F-statistic shows the statistic on the excluded instruments.

# Chapter 2

# Broken homes and empty pantries: The impact of romantic relationship dissolution on household economic resources

**Abstract**

This study investigates the impact of a couple's break-up on the economic resources of the household by studying changes in income and food purchases around the time of separation in a panel of French households. I estimate a household fixed effects model to account for unobserved time-invariant household characteristics while controlling for additional time-varying covariates. Household income and food purchases decrease suddenly and significantly at the time of separation and remain lower than pre-separation levels for several years after the break-up. The decrease in food purchases appears to translate into a slight decrease in the female's body mass index (BMI). While the decline in income is more pronounced for households with higher pre-separation income, the decline in food purchases and BMI mainly affects households in the lowest pre-separation income tercile, suggesting that these changes are due to insufficiency of financial resources rather than individual preferences.

# 1. Introduction

Over the last decades, the number of children growing up in single-parent households in France has steadily increased. The share of single-parent families out of families with children under 25 years old has more than doubled from 9.4% in 1975 to 24% in 2016 (INSEE, 2019a). France is not an isolated case. In the US, for example, over one-quarter of all children under 21 years have one of their parents living outside of their household in 2015 (Grall, 2015). Cross-sectional data show that the average standard of living per person in single-parent families is one-third lower than the average for other families. After redistribution, 20% of single-parent families are considered poor at the poverty line equivalent to 50% of median income, compared to 7% of couples with children INSEE (2019b). This has important implications for public policy, given that lower economic resources are associated with worse adult and children's outcomes including poorer psychological and physical health, lower academic achievement, and more behavioural problems (Amato, 2000, 2014; McLanahan et al., 2013; Tach and Eads, 2015). Well targeted policies supporting vulnerable families are likely to avoid costly negative outcomes in future (OCDE, 2011) but necessitates information on how and when precisely the family's needs are affected.

A large body of research has investigated the economic consequences of union dissolution, showing that women experience significant declines in income following a separation. Estimates of the decline in income one year after divorce range from 23% to 40% (Hoffman, 1977; Duncan and Hoffman, 1985b; Bianchi and McArthur, 1991; Holden and Smock, 1991; McLanahan and Sandefur, 1994; Peterson, 1996; Galarneau and Sturrock, 1997; McKeever and Wolfinger, 2001; Avellar and Smock, 2005; Tach and Eads, 2015). For men, the effects have been found to be more heterogeneous and overall less severe (Smock, 1994; Galarneau and Sturrock, 1997; McManus and DiPrete, 2001). Concerning food purchases, some few studies investigate associations between changes in marital status and eating behaviours focusing mostly on a limited set of food items (Lee et al., 2004; Vinther et al., 2016). In most studies, the effects of separation on household income have been estimated by comparing changes in income across two time periods, before and after the break-up occurs. However, when the comparisons are restricted to only two points in time they overlook the possibility of dynamic adjustments to changes in relationship status. It is thus difficult to draw firm conclusions about the time-path of the economic consequences of separation Teachman and Paasch (1994); Page and Stevens (2004). Estimates based on simple "before and after" comparisons are also likely to be biased if the effect is not immediate and constant over time (Laporte and Windmeijer, 2005). In addition, most of the studies do not include a control

group.

Dynamic adjustments to changes in relationship status are more rarely investigated as the necessary data - longitudinal data on a large representative number of households including information on both relationship status and household economic resources for an extended period of time - are not always readily available.Among the rare studies which examine the time-path of income and consumption following divorce, many are based on non-representative, dated samples and, most importantly, do not employ regression analysis which means that there is no adjustment for any time-varying covariates (Weiss, 1984; Duncan and Hoffman, 1985a,b; Peterson, 1989; Stirling, 1989). There exist only few recent longitudinal studies employing regression analysis to investigate the time-path of income and consumption after separation. Using US data, Page and Stevens (2004) study household income and food expenditures by estimating household fixed effect models and controlling for additional time-varying covariates. Fisher and Low (2016) also estimate household fixed effects models to investigate changes in income separately for low, middle and high income households in the UK but they do not control for time-varying household characteristics. De Vaus et al. (2014), De Vaus et al. (2017) and Fisher and Low (2009) study the time-path of income using data from Australia, six OECD countries and the UK, respectively. While controlling for some observable household and individual characteristics, they do not account for unobserved heterogeneity. To this point, I am not aware of any recent study investigating the time-path of income and consumption following partnership dissolution in France.

In this study, I use data from a panel of French households to investigate the impact of a couple's break-up on household income and food purchases as proxies for household economic resources. I estimate a household fixed effects model to account for any unobserved time-invariant household characteristics and control for a range of time-varying household covariates including the employment status of both spouses. I look at changes in income and food purchases in the years shortly before, during and after separation relative to a reference period of 3 years or more preceding the event to account for the possibility of dynamic adjustments to changes in relationship status. This avoids the potential bias from simple "before and after" comparisons if the effect is not immediate and constant over time. I further examine whether the changes in food purchases translate into changes in the body mass index (BMI) of the household members or changes in the healthiness of their diets in terms of the share of unhealthy food products purchased. Similarly to Fisher and Low (2016), I perform heterogeneity analyses by grouping households according to their average pre-separation per-capita household income. In addition, I estimate the effects separately for households with and without children.

I find that household income as well as food purchases decrease suddenly and significantly at the moment of separation and remain significantly lower than pre-separation levels several years thereafter. The effects I find in the French data are less pronounced than what has been reported by Page and Stevens (2004) using US data. While I find that household income declines by 23% in the year following separation and food purchases by around 17%, Page and Stevens (2004) reports a decline in income by 50% and a drop of 35% in food purchases. Albeit less strong, the effects of separation appear to last longer for the French households compared to their American counterparts. I do not find evidence for a recovery over time whereas Page and Stevens (2004) find that food purchases recover partially after 6 years as they are then only 6% lower than pre-separation level and household income is 23% lower than pre-separation levels. Page and Stevens (2004) attributes this recovery mainly to re-marriage which I rarely observe in the French data. The decline in food purchases is accompanied by a slight decrease in the body weight of the newly single female.I further find that the share of unhealthy food purchases increases around the time of separation, suggesting that households adopt less balanced diets. The decrease in food purchases and female partner's BMI could have positive effects on health through a reduction in overweight. However, the adoption of less balanced diets is likely to have negative health consequences.

The decline in income is more pronounced for households with higher pre-separation income levels. This is consistent with results from Fisher and Low (2016) who find that women in the highest income households before divorce suffer the largest and most persistent falls in their standard of living compared to those from the lowest income households. However, I find that the decrease in food purchases and BMI mainly affects households in the lowest pre-separation income tercile. If we assume that preferences for weight loss or the incidence of separation-related depression do not differ across households with respect to pre-separation income levels, finding stronger declines in food purchases and female partner's BMI in the poorest tercile of the households but not in the richest tercile suggests that these changes are due to insufficient financial resources. While Fisher and Low (2016) identify higher-income households as particularly affected, my results point toward low-income households being particularly vulnerable as they appear less able to smooth necessary consumption. This result underlines the importance of investigating not only household income but also consumption to make statements about which households are particularly exposed to post-separation hardship. Changes in household food purchases are arguably a more direct measurement of changes in economic resources than changes in income as the former inform us about the ability to maintain a certain level of necessary expenditures in the presence of a negative income shock.

# 2. Method

## 2.1. Data

I use data on household characteristics and food purchases from a representative sample of 61,000 French households collected by *Kantar Worldpanel* covering the period 2005 to 2014.[1] This data include information on household composition, household income (pensions and alimony payments are counted as well),and the socioprofessional category, age, gender, height, weight, education level, and occupation status of each household member. Information on household food purchases include product type, quantity, price and purchase date. All data concerning individual and household characteristics are updated on a yearly basis. Therefore, the time interval used in this study is the year. Household food purchases are constructed as the amount of annual product purchases, both in terms of total expenditures denominated in Euro and total quantity purchased measured in grams. I further define the share of unhealthy food products as the amount of annual purchases of ready meals products (pizza, sauerkraut, cassoulet, etc.), salt-fat products (finger food, chips, crackers, appetisers) and sugar-fat products (candy, chocolate, cookies, pastry, ice cream, jam, etc.) over the total amount of annual household food purchases. I use the information on weight, height and age to construct household calorie needs and the body mass index (BMI) of each household member[2]. No data is available concerning purchases of food eaten away from home but households report the number of meals typically eaten at home by day of the week. This variable serves me as a proxy for household eating habits in terms of food eaten at home. Table A1 provides descriptive statistics.

The data do not include direct information on the marital status of the household members but individuals are attributed codes according to their status within the household. Status 1 corresponds to the female partner (the panellist responsible for food purchases) and status 2 to the male partner (the household head), whereas status 3 and 4 denote additional female and male household members (mainly children). I define separation as the departure from the household of an individual of status 1 or status 2.[3] I am therefore looking at

[1] Kantar is a private company specialised in the construction of consumer panels and analysis for market research purposes similar to AC Nielsen in the US. The firm provides households with hand-held scanners which are used to scan all food purchases of every good with a bar code. Food items without a bar code are entered manually by the panellist. For more information, refer to the *Kantar Worldpanel* website at `https://www.kantarworldpanel.com/global/Consumer-Panels`.

[2] Body mass index (BMI) is calculated by dividing the individual's weight by the square of height and is commonly used to measure corpulence.

[3] It is possible that the departure of an individual is due to death rather than separation. However, most

the separation of both cohabiting and married couples without being able to distinguish between these groups. Out of the total of 1,447 households for which I observe separation, only 230 are cases of a female partner leaving the household. The effects I estimate are therefore mainly the impact of a male partner leaving the household. On average, 0.4% of the households in the sample separate in any given year.[4] This separation rate is lower than the rate observed at the level of the French general population which is situated around 1%.[5] This could be due to households dropping out of the sample when faced with difficult times such as separation. If this is indeed the case, then I am not observing the effects of separation on the hardest-hit households, meaning that my estimates could be lower bounds for stronger true effects.

### *2.2. Empirical Strategy*

Using data for households in which couples separate at some point during the observation window and a comparison group of household in which the couple did not separate, I estimate the following household fixed effects model

$$R_{ht} = \beta X_{ht} + \gamma D_{ht} + \alpha_h + \rho_t + \epsilon_{ht}.$$

where $R_{ht}$ denotes the measure of household economic resources in terms of household income or food purchases of household $h$ at time $t$. The separation of the cohabiting couple is captured by $D_{ht}$ which is a vector of dummy variables indicating that a separation has taken place in a future, current, or previous year. While the household fixed effects $\alpha_h$ control for any *time-invariant* household characteristics other *time-varying* household characteristics could still influence both the probability of separation and household economic resources. I therefore control for a vector of time-varying household covariates, $X_{ht}$. This vector includes family size to account for changes in family composition that accompany resource changes[6] in addition to the age and the employment status of both spouses. Controlling for the

often, the end of the union follows a separation, with few deaths occurring before age 65 (INED, 2019; INSEE, 2015). The results are robust when I consider a sub-sample of younger individuals.

[4]There are 61,204 different households in the sample out of which I observe 45,610 for at least 2 years and for which I can potentially observe separation. I count 1,447 separations in the years 2006 to 2013 (I cannot observe separations in the year 2005 and 2014 because I do not observe household composition in 2004 and 2015). This comes to 1,447/8 households separating per year over the 45,610 households in which I can potentially observe separation.

[5]According to data from INSEE, an average of 290,000 couples separate in a year between 2009 and 2012 (INSEE, 2015) which corresponds to roughly 1% of the households being concerned with separation in any given year considering there are 28,800,000 households in France (number in 2014 according to INSEE).

[6]This variable captures changes in household size other than the departure of one of the spouses.

employment status is important as job loss could be both correlated with the probability of separation and with household income and consumption. The year fixed effects $\rho_t$ control for economy-wide income and consumption changes over time, including business cycle effects and trends in income and consumption over time. Finally, $\epsilon_{ht}$ is the random error. In some of the regressions, the outcome variable $R_{ht}$ is replaced with the share of unhealthy food products purchased or the BMI of the household members as proxies for the potential health effects related to the changes in economic resources. In the regressions on food purchases, I include in addition household calories needs constructed as the sum of the basal metabolic rate (BMR) of each family member using their height, weight, age and gender, and the average meals eaten at home per capita in a typical week as measure for potential changes in the proportion of food eaten at home.

I estimate a household fixed effect model to account for any unobserved time-invariant household characteristics that may be correlated with both the probability of separation and income or food consumption. If couples from households with lower economic resources are more susceptible to separate, for example, then failing to control for household fixed effects will yield estimates that will be biased toward finding larger losses. Including a control group of households in which the couple does not separate is important to estimate how much more economic resources households would have had if the couple had remained together. Most previous studies simply compared household income in a particular period before the separation to income in a particular period after the separation and therefore make no such comparison.

Other unobserved time-varying characteristics could still lead to biased estimates. For example, previous research has shown that marital dissolution is associated with an effect on health that occurs before the actual change in marital status as well as an effect at the time of dissolution (Blekesaune and Barrett, 2005; Laporte and Windmeijer, 2005).[7] Increased intra-household conflict which remains unobserved could also impact household consumption prior to separation. Unfortunately, I cannot control for such unobserved changes but I account for the possibility of dynamic adjustments in household income and food consumption by using a vector of dummy variables, $D_{ht}$, indicating that separation takes place in a previous, current or future year. This specification should capture any changes in household income and purchases over time including changes related to unobserved time-varying characteristics prior to separation. If, for example, a negative health shock leads to loss of income and reduced consumption prior to the separation I am likely to observe these changes. However,

[7] Others find that sickness appears to be a consequence of rather than a reason for separation Dahl et al. (2015).

if the changes in health, income, consumption and family composition happen simultaneously (within the same year) I cannot tell apart the effect of the health shock from the effect of separation.

Accounting in such a way for dynamic adjustments is important. A step variable approach may overstate or understate the average annual losses associated with separation depending on which "before" and "after" years are chosen. If household experience losses in economic resources prior to the separation, a variable comparing the average level of economic resources before and after the separation would ignore the preceding effect and underestimate the immediate effect. Investigating dynamic adjustments is also interesting as the short-term effects of separation may differ from the long-term effects(Page and Stevens, 2004; Laporte and Windmeijer, 2005). A step variable could potentially overestimate the long-term effect if households recover relatively quickly after the separation. These are important considerations for policy makers who want to design optimal policies depending on the timing, strength and duration of the effects of separation. I look at changes in income and food purchases in the years shortly before, during and up to 9 years after separation relative to a reference period of 2 years or more preceding the event.

I use both household income and food purchases as proxies for household economic resources. Besides the measures of economic resources, I use diet composition in terms of the share of unhealthy food products purchased and the BMI of the different household members as proxies for potential health effects related to the changes in economic resources. It has been argued that consumption measures are preferable to income measures because income understates the financial resources available, and because consumption is a more direct measure of well-being (Meyer and Sullivan, 2004; Page and Stevens, 2004). Food expenditure is the sort of necessary expenditure that is interesting to policy makers. However, it is also relatively inelastic with respect to changes in economic resources. Household are likely to use their savings or to reallocate their budget by diminishing other expenses such as leisure and durable goods to maintain some minimum threshold of food consumption. I therefore expect to see fewer variation in food purchases compared to any other kind of consumption.

I conduct heterogeneity analyses for which I group households according the their pre-separation per-capita income the presence of children, the sex, employment status and the relationship status (eventual re-partnering of the remaining spouse) to investigate whether separation impacts economic resources more severely in some types of households. If saving and budget reallocation are important mechanisms, I expect food consumption to be most

responsive to income shocks in low-income households, which may be less able to smooth their consumption. Differential effects in households with and without children could be due to different childcare arrangements and labour supply response of parents.

## 3. Results

Columns 1 and 2 of Table 1 show how the main variables of interest - household income and food purchases as proxies for household economic resources - evolve in the period ranging from 1 year before and up to 9 years after separation relative to the reference period of 2 years or more before the break-up. Relative to the reference period, household income starts to decline by 3.9% in the year just before separation. It then drops sharply by 15.2% and 22.7% in the year of separation and the year just following the event and remains 21% to 25% below its pre-separation level thereafter. The quantity of household food purchases decline by 6.1% in the year of separation, albeit this drop is only statistically significant at the 5% level. Food purchases then drop by 17.2% and 19.2% in the first and second year after separation, respectively. After that, food purchases remain at least 16% lower relative to the pre-separation reference period. The changes in food expenditures mirror the changes in food quantities purchased and are therefore not shown here.

Not only do I find that household income and food purchases decrease after separation, but it also appears that these changes are accompanied by decreases in the weight of the female partner. The evolution of the female's BMI is shown in Column 3 of Table 1. In the year prior to separation, the BMI starts to decline slightly by 0.4%. In the year of separation and the 2 following years, the BMI drops is around 1% lower than in the pre-separation period. From year three onward, the female's BMI appears to have recovered to its pre-separation level. I do not find any effects on children's BMI. Finally, I find evidence for changes in diet composition around the moment of separation which is reported in Column 4 of the same Table. In the years before separation, the share of unhealthy food purchased over the total quantity of food purchased increases by about 5% and then increases sharply in the year of separation to a level 10% higher relative to the reference period. During the entire period of observation, the share of unhealthy food purchases remains more than 6% higher than its pre-separation level. Finding a decrease in BMI suggests that overall caloric intake has reduced following the decline in food purchases, despite the shift to a less healthy diet consisting of more salty, sweet, fatty and convenience foods, which are relatively calorie-dense food products.

Table 1: Evolution of household income, food purchases and partner BMI around the time of separation

| | Income | Food purchases | Partner's BMI | Share unhealthy food |
|---|---|---|---|---|
| 1 year before | -0.0389*** | 0.0275 | -0.00403* | 0.0494*** |
| | (0.010) | (0.019) | (0.002) | (0.012) |
| Year of separation | -0.152*** | -0.0606* | -0.0102*** | 0.108*** |
| | (0.012) | (0.025) | (0.002) | (0.015) |
| 1 year after | -0.227*** | -0.172*** | -0.0117*** | 0.103*** |
| | (0.014) | (0.028) | (0.002) | (0.017) |
| 2 years after | -0.231*** | -0.192*** | -0.00884** | 0.0780*** |
| | (0.016) | (0.033) | (0.003) | (0.021) |
| 3 years after | -0.214*** | -0.167*** | -0.000505 | 0.0651* |
| | (0.019) | (0.041) | (0.004) | (0.027) |
| 4 to 9 years after | -0.250*** | -0.175*** | 0.00485 | 0.0818** |
| | (0.024) | (0.043) | (0.005) | (0.031) |
| Observations | 203840 | 179140 | 178252 | 178691 |
| $R^2$ | 0.111 | 0.030 | 0.013 | 0.032 |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Household fixed effects | Yes | Yes | Yes | Yes |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered over household in parenthesis. All models include household and year fixed effects and controls for household size, activity status and age of both spouses. Regressions on food purchases include in addition household calorie needs and the average number of meals eaten at home in a week.

All models include household fixed effects, year fixed effects and a range of controls for time-varying household and individual characteristics including household size, employment status and age of both spouses. In the regressions on food purchases, I add controls for total household calorie needs and the average number of meals eaten at home in a typical week to adjust for potential changes in the proportion of food eaten at home relative to food eaten away from home. The results remain qualitatively similar when I look at different reference periods. Tables A2 and A3 in the Appendix show results up to 2 and, respectively, 3 years before separation compared to a reference period of 3 or, respectively, 4 years or more prior to separation. Figure A1 to A3 in the Appendix illustrate these results graphically. The results are also robust to using different income and food consumption equivalent scales such as per capita income and food purchases as shown in Table A4 in the Appendix or income and food purchases divided by a consumption unit measure to account for household economies of scale as shown in Table A5 in the Appendix.

To investigate heterogeneous effects with respect to household income, I divide households into terciles according to household income per capita averaged over the pre-separation period. Panel A in Table 2 shows the results for first income tercile including the poorest households, panel B presents results for the second tercile whereas panel C reports results for the third tercile which means the richest households. Household income declines more strongly in households with higher pre-separation income. This is not surprising if the higher pre-separation income reflects the relatively high salary of the spouse who then leaves the household. Despite the relatively smaller decrease in household income experienced by the household in the first income tercile, the effect of separation on food purchases in these households is stronger than in households with higher pre-separation income. In the first and second year after separation, the poorest households reduce their food purchases by over 30% compared to the pre-separation reference period. For households in the second and third income tercile, food purchases decrease by at most 15% with many of the effects not being statistically significant. The effects on the female's BMI are also concentrated in households from the first income tercile for which I observed a reduction of around 2%. The BMI does not appear to change in households from the second and third income tercile as the coefficients are mostly not statistically significant and close to zero. The share of unhealthy food relative to the total quantity of food purchased increases for all households, albeit less strongly in households from the first income tercile. Households belonging to the first income tercile already consume a higher share of unhealthy foods prior to separation compared to households from the second and third income terciles and may therefore have less margin to increase this share even further at the time of separation.

Table 2: Evolution of outcome variables around separation, by pre-separation household income

| | Income | Food purchases | Partner's BMI | Share unhealthy food |
|---|---|---|---|---|
| | *Panel A - First income tercile* | | | |
| 1 year before | -0.0705*** | 0.00207 | -0.0115** | 0.0377 |
| | (0.018) | (0.035) | (0.004) | (0.021) |
| Year of separation | -0.0982*** | -0.155*** | -0.0187*** | 0.0695** |
| | (0.020) | (0.046) | (0.004) | (0.024) |
| 1 year after | -0.134*** | -0.331*** | -0.0234*** | 0.0769** |
| | (0.022) | (0.059) | (0.005) | (0.028) |
| 2 years after | -0.125*** | -0.309*** | -0.0170** | 0.0249 |
| | (0.028) | (0.063) | (0.006) | (0.036) |
| 3 years after | -0.0767* | -0.289*** | -0.00532 | -0.0298 |
| | (0.030) | (0.087) | (0.008) | (0.052) |
| 4 to 9 years after | -0.134*** | -0.160* | 0.0151 | 0.0303 |
| | (0.039) | (0.063) | (0.012) | (0.052) |
| | *Panel B - Second income tercile* | | | |
| 1 year before | -0.0326* | 0.0437 | -0.00342 | 0.0751*** |
| | (0.017) | (0.032) | (0.003) | (0.021) |
| Year of separation | -0.150*** | -0.00616 | -0.00987** | 0.141*** |
| | (0.020) | (0.043) | (0.003) | (0.025) |
| 1 year after | -0.255*** | -0.134** | -0.00699 | 0.118*** |
| | (0.024) | (0.047) | (0.004) | (0.030) |
| 2 years after | -0.263*** | -0.122* | -0.00614 | 0.106** |
| | (0.028) | (0.051) | (0.004) | (0.038) |
| 3 years after | -0.275*** | -0.0929 | 0.00247 | 0.0912* |
| | (0.034) | (0.058) | (0.006) | (0.041) |
| 4 to 9 years after | -0.316*** | -0.113 | -0.00165 | 0.0681 |
| | (0.042) | (0.082) | (0.008) | (0.052) |
| | *Panel C - Third income tercile* | | | |
| 1 year before | -0.00891 | 0.0255 | 0.000954 | 0.0333 |
| | (0.016) | (0.031) | (0.003) | (0.019) |
| Year of separation | -0.200*** | -0.0320 | -0.00409 | 0.110*** |
| | (0.020) | (0.036) | (0.003) | (0.023) |
| 1 year after | -0.278*** | -0.0690* | -0.00680 | 0.111*** |
| | (0.022) | (0.034) | (0.004) | (0.029) |
| 2 years after | -0.289*** | -0.153** | -0.00512 | 0.0980** |
| | (0.026) | (0.052) | (0.004) | (0.032) |
| 3 years after | -0.270*** | -0.130* | 0.0000534 | 0.122** |
| | (0.032) | (0.066) | (0.006) | (0.042) |
| 4 to 9 years after | -0.288*** | -0.246*** | 0.00175 | 0.136** |
| | (0.042) | (0.072) | (0.006) | (0.053) |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered over household in parenthesis. All models include household and year fixed effects and controls for household size, activity status and age of both spouses. Regressions on food purchases include in addition household calorie needs and the average number of meals eaten at home in a week.

One possible interpretation of these results is that households adopt a less healthy, potentially higher calorie diet, but overall calorie intake still decreases due to lower food purchases, with particularly strong effects among low-income households, where the change in diet is less pronounced and the decrease in food purchases more substantial. The results are qualitatively similar when using the reference period of 3 years or more prior to separation (see Table A6 in the Appendix).

I also find that changes in all outcome variables are larger in households where children are present at the time of separation and, in particular, in households with minor children, compared to households with adults only. See Tables A7 and A8 in the Appendix. Income declines by at most 18% from its pre-separation level in households without children compared to decreases of over 30% in households with children. Food purchases drop by a maximum of 16% in households without children, whereas households with children reduce their food purchases by over 24% and households with minor children reduce them by over 27% in the first two years after separation. Households with children are more likely to belong to the first and second income tercile compared to adult-only households. However, the differences between these family types are not driven by different pre-separation income levels. The stronger effects in households with children could be due to lower labour market participation of parents who need to reconcile market labour with childcare. It may also be related to the fact that children are potentially registered in the household although they are not present at all times in case the spouses agreed on alternating custody. My data does not allow me to differentiate between these effects. Looking at income terciles *within* each family type, I find that the effects are stronger in the poorest tercile of households with children compared to the poorest tercile of adult-only households. Results are less strong for the second and third income terciles but again relatively stronger for households with children compared to adult-only households.[8]

Further heterogeneity analyses with respect to the sex, employment status and relationship status of the remaining partner remain inconclusive. Estimating the effects separately for the different sub-groups yield results which are not statistically significant, probably due to limited statistical power. I observe only 230 cases in which the female partner leaves the household, 132 cases in which the remaining partner is inactive at the moment of separation and only 116 cases in which the remaining partner starts a new relationship during the period of observation.

# 4. Discussion and conclusion

This paper provides evidence for long-lasting declines in the economic resources of households after the separation of the couple. Using panel data on household characteristics and food purchases in France, I estimate a household fixed effects model to account for any unobserved time-invariant household characteristics while controlling for additional time-

[8] Tables are made available upon request.

varying covariates. Household income as well as food purchases decrease suddenly and significantly at the moment of separation and remain significantly lower than pre-separation levels for several years after the break-up. The decline in food purchases is accompanied by a slight decrease in the female's BMI. The share of unhealthy food purchases increases around the time of separation, suggesting that households adopt a less healthy diet. While the decline in income is more pronounced for households with higher pre-separation income levels, the decrease in food purchases and BMI mainly affects households in the lowest pre-separation income tercile.

Declines in household income and food purchases at the time of separation have previously been reported in the literature. The results from this study are most comparable to the findings from Page and Stevens (2004) who also estimate household fixed effect models but using data from the US. Page and Stevens (2004) report that household income and food purchases decrease during and several years after separation but the magnitude of the decline in their data is larger compared to the decline I find in the French data. While I find that household income declines at most by 23% in the year following separation and food purchases by around 17%, Page and Stevens (2004) reports a decline in income by 50% and a drop of 35% in food purchases in the year following separation. This difference in the strength of the effect could be due to the more generous welfare systems in France compared to the US. Public spending on family benefits including spending in cash, services and tax breaks in 2017 amounts to over 3.5% of GDP in France whereas it is only about 1% in the US (OECD, 2017). Another possibility is that the differences are due to the different time periods considered.[9] The effects appear to last longer for the French households. I do not find evidence for a recovery in the income and consumption losses over time contrary to Page and Stevens (2004) who find that households partially these losses. After 6 years, food consumption is 6% lower and income 23% than pre-separation level compared to the initial drops of 35% and 50%. Page and Stevens (2004) attributes this recovery to the fact that a substantial fraction of divorced mothers remarries. I rarely observe such re-partnering in the French data. Finding a decline in the female's BMI is consistent consistent with some previous studies (Lee et al., 2004; Eng et al., 2005) but results have been ambiguous as other studies point rather towards weight gain after divorce or separation (Mata et al., 2018).

The decline in income is more pronounced for households with higher pre-separation income levels. This is consistent with results from Fisher and Low (2016) who find that women in the highest income households before divorce suffer the largest and most persistent falls in their standard of living compared to those from the lowest income households. However, I find that the decrease in food purchases and BMI mainly affects households in the lowest pre-separation income tercile. While Fisher and Low (2016) identify higher-income households as most affected, my results point toward low-income households being particularly vulnerable as they appear less able to smooth necessary consumption. This underlines the importance of investigating not only household income but also consumption to see which households are particularly exposed to post-separation hardship. Changes in household food purchases are arguably a more direct measurement of changes in economic resources than

[9] Page and Stevens (2004) use data from the 1968 through 1993 waves of the Panel Study of Income Dynamics whereas I use data on households from 2005 to 2014.

changes in income as these changes inform us about the ability of the household to maintain certain necessary expenditures in the presence of a negative income shock.

The household fixed effects pick up any time-invariant household characteristics, whereas the vector of time-varying household covariates controls for some of the changes in household characteristics that could be both correlated with the probability of separation and the outcome variables and therefore lead to biased estimates. Job loss, for example, could be both correlated with the probability of separation and with household income and consumption but is controlled for in all of the regressions. However, bias may still arise from other unobserved time-varying household characteristics, such as for example the health of the household members. Sudden illness of one of the spouses could both increase the probability of separation and reduce household income and food purchases. Assuming that such shocks do not lead instantaneously to physical separation - partners may first try to cope with the new situation or need at least some time to prepare for leaving the household - but that household income and consumption are affected almost immediately, I should observe changes in income and consumption prior to actual separation. Yet, this is not what I observe in the data. Household income and the female partner's BMI are relatively stable in the years prior to separation. Food purchases actually increase before the sudden and sizeable drop in the year following the break-up.

The declines in food purchases and the female's BMI could be due to changes in household preferences rather than a result of a negative income shock related to separation. The newly single individual may want to buy less food and lose weight to increase her chances of finding a new partner. Depression and loss of appetite could also potentially be the reason for decreased food purchases and weight loss rather than a decrease in household financial resources. Individuals could also change the way they report food purchases. [10] However, such explanations become less plausible considering that the decline in household food purchases and female's BMI are concentrated in households from the lowest pre-separation income tercile and that the effects appear to be as good as absent in the households from higher terciles. If we assume that preferences for post-separation weight loss, the incidence of separation-related depression and loss of appetite, and food and weight recording behaviour do not differ across households with respect to their pre-separation per capita household income, then finding stronger declines in food purchases and female's BMI in the poorest tercile of the households but not in the richer terciles suggests that these changes are due to insufficiency of financial resources. The results are consistent with the hypothesis that food expenditure is relatively income inelastic as households use their savings to maintain some minimum threshold of food consumption. Households with lower pre-separation income probably had less capacity to save and could therefore not smooth their consumption at the time of separation whereas richer households were better able to cushion the effects. This suggests that public assistance is not sufficient to eliminate the economic suffering associated with partnership dissolution, even in a country with relatively strong welfare safety nets such as France.

[10] Note that I control for the number of meals so that I control for the proportion of food eaten at home/away from home. So this is not a question of changing eating behaviour in terms of eating out more often.

The decrease in food purchases and the female partner's weight loss following separation, although potentially involuntary, could have positive effects on health, for example through a reduction in overweight. I find some evidence that spouses whose BMI is situated in the lowest tercile prior to the separation appear not to lose weight as the changes in BMI are concentrated in the second and third BMI terciles. However, I also find that the share of unhealthy food purchases increases shortly before, during and after separation, suggesting that households adopt less balanced diets. I am not able to make any statement about the net effects on health.

This paper presents evidence for important declines in economic resources after separation from which households do not recover several years after the break-up. While the decline in income is more pronounced for households with higher pre-separation income, the decline in food purchases and BMI mainly affects households in the lowest pre-separation income tercile, suggesting that poor households are not able to smooth even the most necessary kind of consumption across the income shock. The existing welfare safety net in France appears insufficient to eliminate the economic suffering associated with partnership dissolution. Although the phenomenon is not sufficiently documented, it is estimated that 35% of individuals do not receive the child support payments that have been legally granted (Auvigne et al., 2016). The government's efforts to decrease the number of child support payment arrears through the creation in 2017 of the Agency for the Recovery of Child Support Arrears (ARIPA for the French "Agence de recouvrement des impayés de pension alimentaire") have been judged insufficient.[11] Before or in addition to considering an eventual increase in public assistance or mandatory child support payments, policy makers should make sure that the current legislation is fully enforced. Such policy is not only a question of fairness to assure that both parents share the responsibility for their common dependants but mitigating the decline in economic resources also avoids potentially costly negative outcomes in the future, such a lower human capital accumulation.

[11] See for example `http://www.leparisien.fr/societe/christelle-dubos-nous-voulons-en-finir-avec-l-enfer-des-pensions-alimentaires-impayees-30-04-2019-8063001.php`.

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Table A1: Summary statistics

| | Control group | | | Treatment group | | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | n | Mean | Std. Dev. | n |
| Household size | 2.64 | 1.38 | 195133 | 2.44 | 1.25 | 8707 |
| Age Spouse 1 | 46.63 | 15.32 | 195133 | 50.34 | 16.2 | 8707 |
| Age Spouse 2 | 48.13 | 15.42 | 195133 | 50.76 | 17.31 | 8707 |
| Spouse 1 is inactive = 1 | 0.3 | 0.46 | 195133 | 0.36 | 0.48 | 8707 |
| Spouse 2 is inactive = 1 | 0.25 | 0.43 | 195133 | 0.34 | 0.47 | 8707 |
| Household calorie needs | 3543 | 1808 | 182682 | 3214 | 1655 | 8312 |
| Meals eaten at home per day | 2.19 | 1.18 | 181474 | 2.06 | 1.05 | 8495 |
| Household income | 2650.57 | 1433.85 | 195133 | 2439.2 | 1328.1 | 8707 |
| Quantity of food purchased | 581845 | 439243 | 195133 | 662913 | 416899 | 8707 |
| BMI spouse 1 | 24.89 | 4.87 | 182163 | 24.84 | 4.81 | 7976 |
| Share of unhealthy food | 0.21 | 0.13 | 195133 | 0.21 | 0.12 | 8707 |

Table A2: Evolution of household income, food purchases, female partner's BMI and share of unhealthy food products purchased over total amount of food purchased around the time of separation

| | Income | Food purchases | Partner's BMI | Share unhealthy food |
|---|---|---|---|---|
| 2 years before | 0.00187 | 0.113*** | -0.000404 | 0.0653*** |
| | (0.009) | (0.020) | (0.002) | (0.012) |
| 1 year before | -0.0382*** | 0.0724*** | -0.00419 | 0.0753*** |
| | (0.011) | (0.021) | (0.002) | (0.015) |
| Year of separation | -0.152*** | -0.0159 | -0.0104*** | 0.133*** |
| | (0.013) | (0.027) | (0.002) | (0.017) |
| 1 year after | -0.226*** | -0.127*** | -0.0119*** | 0.129*** |
| | (0.015) | (0.029) | (0.003) | (0.019) |
| 2 years after | -0.231*** | -0.146*** | -0.00900** | 0.104*** |
| | (0.017) | (0.034) | (0.003) | (0.022) |
| 3 years after | -0.213*** | -0.119** | -0.000678 | 0.0930*** |
| | (0.020) | (0.043) | (0.004) | (0.027) |
| 4 to 9 years after | -0.250*** | -0.125** | 0.00467 | 0.111*** |
| | (0.025) | (0.044) | (0.005) | (0.032) |
| Observations | 203840 | 179140 | 178252 | 178691 |
| $R^2$ | 0.111 | 0.030 | 0.013 | 0.033 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered over household in parenthesis. All models include household and year fixed effects and controls for household size, activity status and age of both spouses. Regressions on food purchases include in addition household calorie needs and the average number of meals eaten at home in a week.

Table A3: Evolution of household income, food purchases and partner BMI around the time of separation

| | Income | Food purchases | Partner's BMI | Share unhealthy food |
|---|---|---|---|---|
| 3 years before | 0.00905 | 0.100*** | -0.000681 | 0.0469** |
| | (0.011) | (0.023) | (0.002) | (0.015) |
| 2 years before | 0.00571 | 0.156*** | -0.000699 | 0.0854*** |
| | (0.012) | (0.023) | (0.003) | (0.017) |
| 1 year before | -0.0343* | 0.116*** | -0.00449 | 0.0956*** |
| | (0.014) | (0.024) | (0.003) | (0.018) |
| Year of separation | -0.148*** | 0.0274 | -0.0107*** | 0.154*** |
| | (0.015) | (0.028) | (0.003) | (0.020) |
| 1 year after | -0.222*** | -0.0831** | -0.0122*** | 0.150*** |
| | (0.016) | (0.031) | (0.003) | (0.022) |
| 2 years after | -0.227*** | -0.102** | -0.00931** | 0.125*** |
| | (0.018) | (0.035) | (0.003) | (0.025) |
| 3 years after | -0.209*** | -0.0727 | -0.000992 | 0.115*** |
| | (0.021) | (0.043) | (0.004) | (0.030) |
| 4 to 9 years after | -0.245*** | -0.0794 | 0.00436 | 0.132*** |
| | (0.026) | (0.045) | (0.006) | (0.034) |
| Observations | 203840 | 179140 | 178252 | 178691 |
| $R^2$ | 0.111 | 0.031 | 0.013 | 0.033 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered over household in parenthesis. All models include household and year fixed effects and controls for household size, activity status and age of both spouses. Regressions on food purchases include in addition household calorie needs and the average number of meals eaten at home in a week.

Table A4: Evolution of per-capita household income, food purchases and partner BMI around the time of separation

| | Income | Food purchases |
|---|---|---|
| 1 year before | -0.0455*** | 0.0240 |
| | (0.010) | (0.019) |
| Year of separation | -0.0179 | 0.0235 |
| | (0.013) | (0.025) |
| 1 year after | -0.0931*** | -0.0851** |
| | (0.015) | (0.028) |
| 2 years after | -0.0971*** | -0.103** |
| | (0.017) | (0.033) |
| 3 years after | -0.0872*** | -0.0821* |
| | (0.019) | (0.041) |
| 4 to 9 years after | -0.114*** | -0.0830 |
| | (0.024) | (0.043) |
| Observations | 203840 | 179140 |
| $R^2$ | 0.350 | 0.031 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered over household in parenthesis. All models include household and year fixed effects and controls for household size, activity status and age of both spouses. Regressions on food purchases include in addition household calorie needs and the average number of meals taken at home in a week.

Table A5: Evolution of household income and food purchases per consumption unit around the time of separation

| | Income | Food purchases |
|---|---|---|
| 1 year before | -0.0484*** | 0.0212 |
| | (0.010) | (0.019) |
| Year of separation | -0.0315* | 0.0143 |
| | (0.012) | (0.025) |
| 1 year after | -0.111*** | -0.0996*** |
| | (0.014) | (0.028) |
| 2 years after | -0.119*** | -0.123*** |
| | (0.016) | (0.033) |
| 3 years after | -0.109*** | -0.101* |
| | (0.019) | (0.041) |
| 4 to 9 years after | -0.139*** | -0.104* |
| Observations | 203840 | 179140 |
| $R^2$ | 0.241 | 0.023 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered over household in parenthesis. All models include household and year fixed effects and controls for household size, activity status and age of both spouses. Regressions on food purchases include in addition household calorie needs and the average number of meals taken at home in a week.

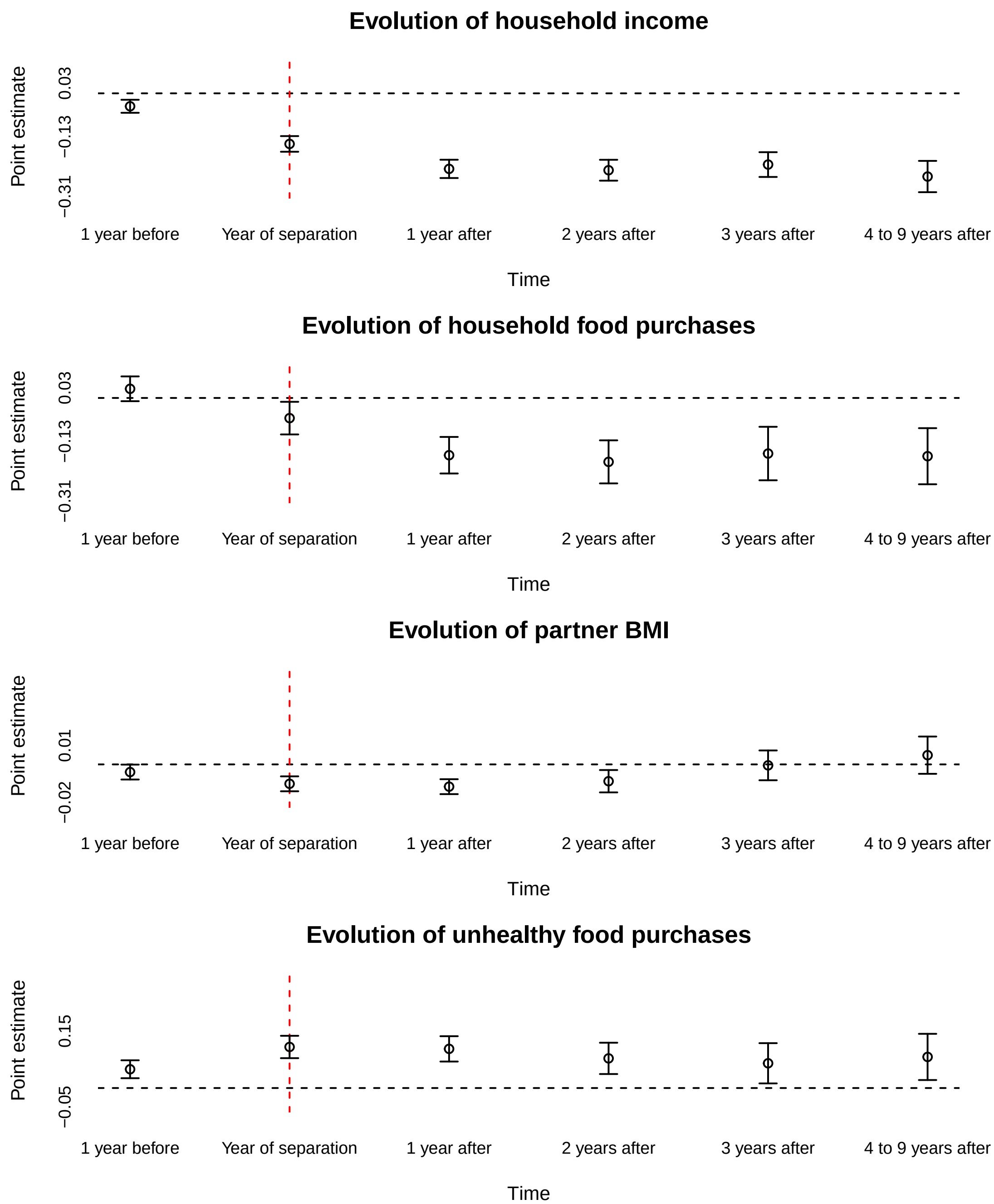


Figure A1.Evolution of household income, food purchases and partner BMI around the time of separation. Point estimates by year from separation relative to 2 years or more before the separation. Brackets show 95% confidence intervals.

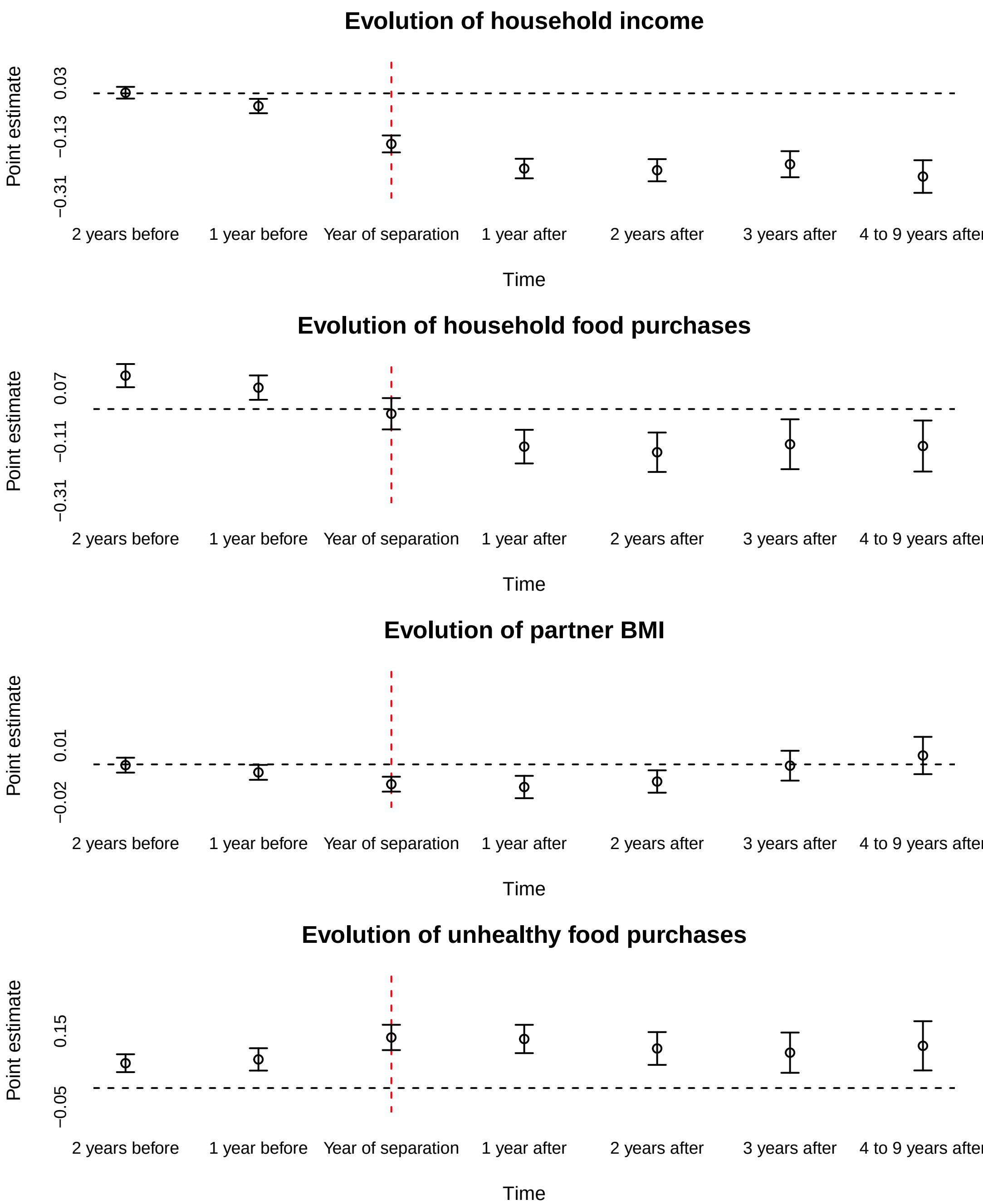


Figure A2.Evolution of household income, food purchases and partner BMI around the time of separation. Point estimates by year from separation relative to 3 years or more before the separation. Brackets show 95% confidence intervals.

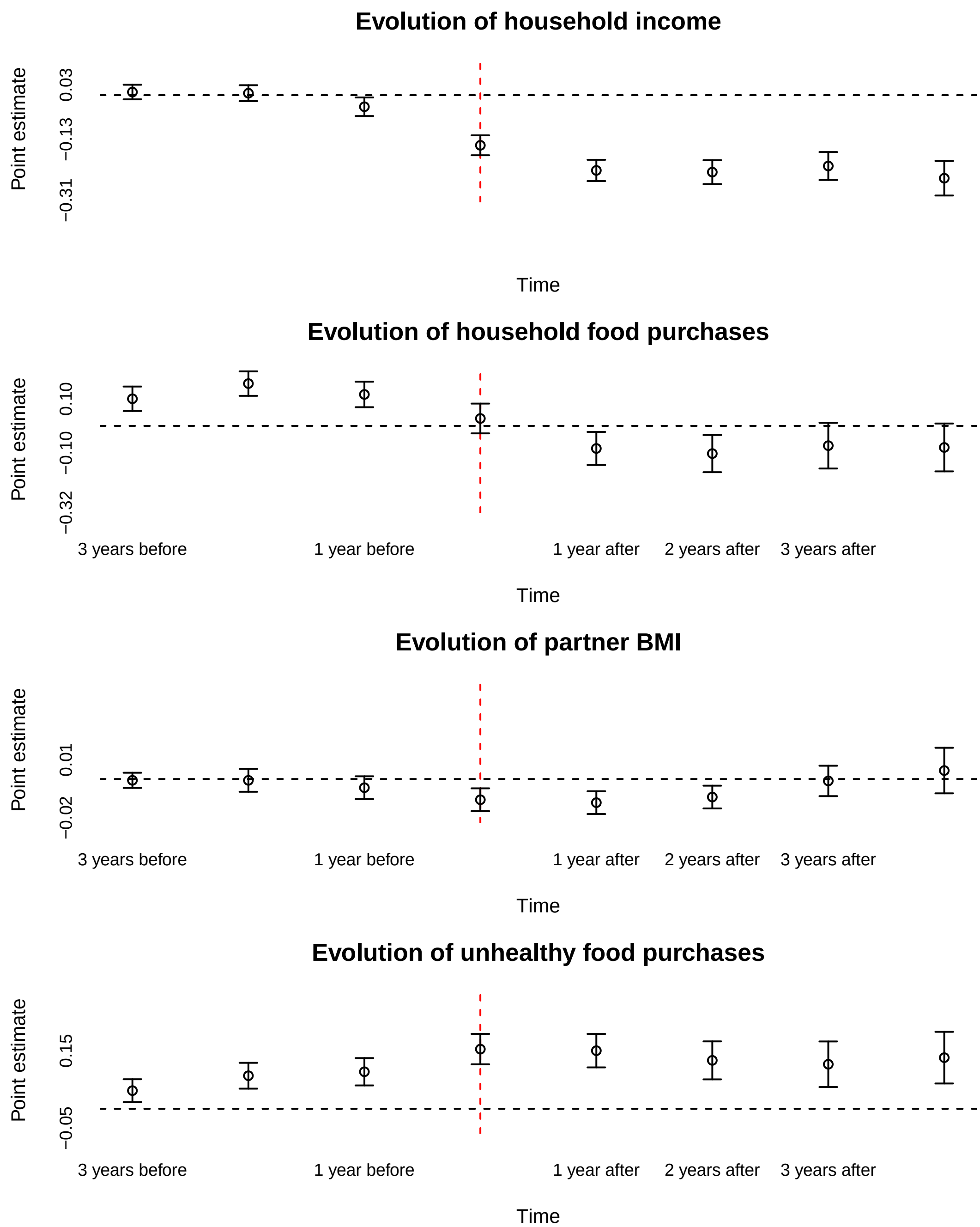


Figure A3.Evolution of household income, food purchases and partner BMI around the time of separation. Point estimates by year from separation relative to 4 years or more before the separation. Brackets show 95% confidence intervals.

Table A6: Evolution of outcome variables around separation, by pre-separation household income

| | Income | Food purchases | Partner's BMI | Share unhealthy food |
|---|---|---|---|---|
| | *Panel A - First income tercile* | | | |
| 2 years before | -0.0165 | 0.0785* | -0.00877* | 0.0631** |
| | (0.018) | (0.036) | (0.004) | (0.020) |
| 1 year before | -0.0774*** | 0.0349 | -0.0152** | 0.0640* |
| | (0.021) | (0.040) | (0.005) | (0.025) |
| Year of separation | -0.105*** | -0.122* | -0.0224*** | 0.0958*** |
| | (0.023) | (0.049) | (0.005) | (0.028) |
| 1 year after | -0.140*** | -0.298*** | -0.0270*** | 0.103** |
| | (0.025) | (0.061) | (0.005) | (0.032) |
| 2 years after | -0.132*** | -0.277*** | -0.0206** | 0.0508 |
| | (0.029) | (0.066) | (0.006) | (0.039) |
| 3 years after | -0.0839** | -0.254** | -0.00910 | -0.00247 |
| | (0.032) | (0.090) | (0.009) | (0.053) |
| 4 to 9 years after | -0.141*** | -0.125 | 0.0112 | 0.0584 |
| | (0.040) | (0.066) | (0.012) | (0.053) |
| | *Panel B - Second income tercile* | | | |
| 2 years before | 0.0119 | 0.0852* | 0.00290 | 0.0689** |
| | (0.017) | (0.037) | (0.003) | (0.023) |
| 1 year before | -0.0279 | 0.0769* | -0.00227 | 0.102*** |
| | (0.020) | (0.035) | (0.004) | (0.026) |
| Year of separation | -0.146*** | 0.0268 | -0.00872* | 0.167*** |
| | (0.023) | (0.045) | (0.004) | (0.029) |
| 1 year after | -0.250*** | -0.101* | -0.00583 | 0.145*** |
| | (0.026) | (0.050) | (0.005) | (0.033) |
| 2 years after | -0.259*** | -0.0882 | -0.00496 | 0.134** |
| | (0.030) | (0.053) | (0.005) | (0.041) |
| 3 years after | -0.270*** | -0.0572 | 0.00370 | 0.120** |
| | (0.036) | (0.059) | (0.006) | (0.044) |
| 4 to 9 years after | -0.311*** | -0.0757 | -0.000379 | 0.0980 |
| | (0.043) | (0.083) | (0.008) | (0.053) |
| | *Panel C - Third income tercile* | | | |
| 2 years before | 0.0107 | 0.158*** | 0.00233 | 0.0612** |
| | (0.013) | (0.030) | (0.003) | (0.021) |
| 1 year before | -0.00491 | 0.0849* | 0.00184 | 0.0562* |
| | (0.017) | (0.035) | (0.003) | (0.024) |
| Year of separation | -0.196*** | 0.0274 | -0.00321 | 0.133*** |
| | (0.021) | (0.040) | (0.003) | (0.026) |
| 1 year after | -0.274*** | -0.00969 | -0.00592 | 0.134*** |
| | (0.023) | (0.038) | (0.004) | (0.031) |
| 2 years after | -0.285*** | -0.0927 | -0.00422 | 0.121*** |
| | (0.027) | (0.055) | (0.004) | (0.035) |
| 3 years after | -0.265*** | -0.0661 | 0.00100 | 0.147*** |
| | (0.033) | (0.068) | (0.006) | (0.044) |
| 4 to 9 years after | -0.283*** | -0.180* | 0.00272 | 0.162** |
| | (0.043) | (0.073) | (0.007) | (0.054) |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered over household in parenthesis. All models include household and year fixed effects and controls for household size, activity status and age of both spouses. Regressions on food purchases include in addition household calorie needs and the average number of meals eaten at home in a week.

Table A7: Evolution of outcome variables, by family type

| | Income | Food purchases | Partner's BMI | Share unhealthy food |
|---|---|---|---|---|
| *Panel A - Households without children* | | | | |
| 1 year before | -0.0285* | 0.00908 | -0.00342 | 0.0339* |
| | (0.012) | (0.023) | (0.002) | (0.016) |
| Year of separation | -0.112*** | -0.0237 | -0.00706** | 0.121*** |
| | (0.015) | (0.030) | (0.002) | (0.019) |
| 1 year after | -0.179*** | -0.122*** | -0.00794** | 0.106*** |
| | (0.017) | (0.032) | (0.003) | (0.023) |
| 2 years after | -0.182*** | -0.167*** | -0.00450 | 0.0797** |
| | (0.020) | (0.040) | (0.003) | (0.028) |
| 3 years after | -0.171*** | -0.146** | 0.000819 | 0.0632 |
| | (0.023) | (0.050) | (0.005) | (0.033) |
| 4 to 9 years after | -0.210*** | -0.151** | 0.00112 | 0.0947* |
| | (0.029) | (0.051) | (0.006) | (0.037) |
| *Panel B - Households with children* | | | | |
| 1 year before | -0.0588*** | 0.0501 | -0.00534 | 0.0706*** |
| | (0.015) | (0.032) | (0.003) | (0.017) |
| Year of separation | -0.215*** | -0.111** | -0.0149*** | 0.0909*** |
| | (0.018) | (0.042) | (0.004) | (0.021) |
| 1 year after | -0.305*** | -0.246*** | -0.0177*** | 0.101*** |
| | (0.021) | (0.049) | (0.004) | (0.024) |
| 2 years after | -0.313*** | -0.228*** | -0.0159** | 0.0762** |
| | (0.025) | (0.055) | (0.005) | (0.029) |
| 3 years after | -0.290*** | -0.198** | -0.00257 | 0.0693 |
| | (0.035) | (0.071) | (0.007) | (0.044) |
| 4 to 9 years after | -0.321*** | -0.213** | 0.0130 | 0.0553 |
| | (0.044) | (0.078) | (0.010) | (0.053) |
| *Panel C - Households with minor children* | | | | |
| 1 year before | -0.0769*** | 0.0857* | -0.00798* | 0.0826*** |
| | (0.018) | (0.040) | (0.004) | (0.019) |
| Year of separation | -0.247*** | -0.105* | -0.0193*** | 0.112*** |
| | (0.021) | (0.052) | (0.004) | (0.023) |
| 1 year after | -0.338*** | -0.265*** | -0.0212*** | 0.135*** |
| | (0.025) | (0.061) | (0.005) | (0.028) |
| 2 years after | -0.341*** | -0.278*** | -0.0195** | 0.127*** |
| | (0.032) | (0.069) | (0.006) | (0.035) |
| 3 years after | -0.297*** | -0.238** | -0.00934 | 0.148** |
| | (0.047) | (0.091) | (0.008) | (0.049) |
| 4 to 9 years after | -0.336*** | -0.331** | 0.000275 | 0.160* |
| | (0.067) | (0.115) | (0.013) | (0.066) |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered over household in parenthesis. All models include household and year fixed effects and controls for household size, activity status and age of both spouses. Regressions on food purchases include in addition household calorie needs and the average number of meals taken at home in a week.

Table A8: Evolution of outcome variables, by family type

| | Income | Food purchases | Partner's BMI | Share unhealthy food |
|---|---|---|---|---|
| *Panel A - Households without children* | | | | |
| 2 years before | -0.000313 | 0.114*** | 0.00116 | 0.0550** |
| | (0.014) | (0.024) | (0.002) | (0.018) |
| 1 year before | -0.0327* | 0.0382 | -0.00359 | 0.0537* |
| | (0.017) | (0.029) | (0.003) | (0.021) |
| Year of separation | -0.113*** | 0.00863 | -0.00754** | 0.152*** |
| | (0.019) | (0.036) | (0.003) | (0.023) |
| 1 year after | -0.185*** | -0.0912* | -0.00806* | 0.138*** |
| | (0.021) | (0.037) | (0.003) | (0.027) |
| 2 years after | -0.186*** | -0.116** | -0.00674 | 0.113*** |
| | (0.024) | (0.043) | (0.004) | (0.032) |
| 3 years after | -0.164*** | -0.0760 | -0.00303 | 0.0805* |
| | (0.028) | (0.054) | (0.005) | (0.036) |
| 4 to 9 years after | -0.215*** | -0.141** | 0.000629 | 0.120** |
| | (0.032) | (0.053) | (0.006) | (0.039) |
| *Panel B - Households with children* | | | | |
| 2 years before | 0.00124 | 0.113** | -0.00158 | 0.0843*** |
| | (0.015) | (0.038) | (0.003) | (0.018) |
| 1 year before | -0.0786*** | 0.0924* | -0.00501 | 0.113*** |
| | (0.019) | (0.037) | (0.004) | (0.022) |
| Year of separation | -0.242*** | -0.0844 | -0.0144*** | 0.127*** |
| | (0.021) | (0.046) | (0.004) | (0.025) |
| 1 year after | -0.322*** | -0.196*** | -0.0181*** | 0.139*** |
| | (0.023) | (0.053) | (0.005) | (0.028) |
| 2 years after | -0.334*** | -0.169** | -0.0147** | 0.108*** |
| | (0.027) | (0.058) | (0.005) | (0.032) |
| 3 years after | -0.314*** | -0.110 | -0.00188 | 0.0982* |
| | (0.036) | (0.072) | (0.007) | (0.046) |
| 4 to 9 years after | -0.331*** | -0.173* | 0.00793 | 0.0588 |
| | (0.049) | (0.084) | (0.011) | (0.055) |
| *Panel C - Households with minor children* | | | | |
| 2 years before | -0.00616 | 0.120** | -0.00492 | 0.107*** |
| | (0.017) | (0.046) | (0.003) | (0.020) |
| 1 year before | -0.0989*** | 0.124** | -0.00955* | 0.129*** |
| | (0.022) | (0.045) | (0.004) | (0.025) |
| Year of separation | -0.276*** | -0.0821 | -0.0207*** | 0.150*** |
| | (0.024) | (0.057) | (0.005) | (0.028) |
| 1 year after | -0.355*** | -0.226*** | -0.0231*** | 0.179*** |
| | (0.027) | (0.066) | (0.006) | (0.033) |
| 2 years after | -0.361*** | -0.216** | -0.0193** | 0.170*** |
| | (0.034) | (0.073) | (0.006) | (0.039) |
| 3 years after | -0.315*** | -0.123 | -0.01000 | 0.206*** |
| | (0.049) | (0.087) | (0.008) | (0.050) |
| 4 to 9 years after | -0.325*** | -0.304** | -0.00795 | 0.199** |
| | (0.081) | (0.118) | (0.012) | (0.072) |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered over household in parenthesis. All models include household and year fixed effects and controls for household size, activity status and age of both spouses. Regressions on food purchases include in addition household calorie needs and the average number of meals taken at home in a week.

# Chapter 3

# The long-run effects of war on health: Evidence from World War II in France

with Olivier Allais and Pascal Leroy

**Abstract**

We investigate the effects of early-life exposure to war on adult health outcomes including cancer, hypertension, angina, infarction, diabetes and obesity. We combine data from the French prospective cohort study E3N on women employed in the French National Education with historical data on World War II. To identify causal effects, we exploit exogenous spatial and temporal variation in war exposure related to the German invasion of France during the Battle of France. The number of French military casualties at the level of the postcode area serves as main measure of exposure. Our results suggest that exposure to the war during the first 5 years of life has significant adverse effects on health in adulthood. A 10 percent increase in the number of deaths per 100,000 inhabitants in the individual's postcode area of birth increases the probability of suffering from any of the health conditions considered in this study by 0.08 percentage points. This is relative to a mean of 49 percent for the sample as a whole.

This article has been published in *Social Science & Medicine* and can be found under the following link: https://doi.org/10.1016/j.socscimed.2021.113812. In a similar paper that is not part of the thesis, "Associations between early-life food deprivation during World War II and risk of hypertension and type 2 diabetes at adulthood", we use the same prospective cohort data to investigate the impact of World War II-related food deprivation on later-life health outcomes. Although no causality is established, the results provide additional evidence for a critical period of development during the first five years of life. The article has been published in Scientific Reports in 2020 and can be found here: https://doi.org/10.1038/s41598-020-62576-w

# 1. Introduction

Wars diminish economic resources and threaten access to food, shelter and health care. Populations are subjected to acute stress related to the experience of violence and disruption of families and communities. Exposure to such hardship is likely to have devastating and potentially long-lasting effects on the health of wartime children. Although exposure to particular environments and experiences appear to influence health development at all stages, it has been suggested that exposure to environmental insults during childhood and adolescence has particularly powerful and long-lasting consequences on health due to the persistence of bio-behavioural attributes that are acquired early in life (Almond and Currie, 2011; Baird et al., 2017; Cunha and Heckman, 2007; Fall and Kumaran, 2019; Halfon and Hochstein, 2002; Hertzman, 1999). Yet, there has been only limited research exploring how early-life exposure to war affects long-term health outcomes in the civilian population. Most of the existing literature focuses on developing countries and shows that the experience of armed conflicts during the pre- or early post-natal period is associated with lower birth weights, lower height-for-age, height, and self-reported health in teenage years and adulthood (Akresh et al., 2012a,b; Alderman et al., 2006; Mansour and Rees, 2012; Minoiu and Shemyakina, 2014).

In this study, we estimate the effects of exposure to World War II (WWII) during childhood and adolescence on objectively measured adult health outcomes including cancer, infarction, diabetes, angina, hypertension and obesity. We use data from the French prospective cohort study E3N on over 28,000 women employed in the French National Education (mainly teachers) born between 1925 and 1950. We combine this demographic and health data with historical data on French military casualties, French prisoners of war (POW) and the Allied bombing of France during WWII. To establish causality, we exploit variation in the intensity of the war across time and space which is plausibly exogenous to individual and family characteristics. More precisely, we compare health outcomes for women born in postcode areas which were intensely affected by the war with women belonging to the same group of birth cohorts but who were born in less affected postcode areas, relative to women from other birth cohorts. Identification strategies of this type are often used in the literature but exploiting data at such a fine geographical level as the postcode area is less common.

Despite the scale and scope of WWII, surprisingly few economic studies exploit the events of this war to investigate the relationship between war exposure and long-term health. Using retrospective data from SHARELIFE for several European countries, Kesternich et al.

(2014) find that experiencing WWII during early-life increases the probability of suffering from diabetes, depression, and heart disease in adulthood. However, health outcomes in this study are self-declared - such data are often argued to be unreliable and subject to self-reporting bias relative to other sources of information, such as medical records or laboratory measurements (Dowd and Todd, 2011; Jürges, 2007) - and treatment is defined at the aggregate (country or region) level, which potentially leads to measurement errors limiting the causal interpretation of the results. Havari and Peracchi (2017) also use SHARELIFE data and find that early-life exposure to hardship related to World War I and II is associated with worse physical and mental health, education, cognitive ability and subjective well-being later in life. Different from Kesternich et al. (2014) and our study, Havari and Peracchi (2017) provide descriptive evidence rather than attempting to uncover causal relationships through quasi-experimental methods.

Our work is closest to Akbulut-Yuksel (2017) who also uses data at a fine geographical level and a similar identification strategy to study the effects of early-life exposure to warfare on adult health. Akbulut-Yuksel (2017) considers the impact of Allied bombing in Germany, using the German Socio-Economic Panel together with data on air bombing to exploit city-by-cohort variation in the intensity of exposure. She finds that individuals exposed in-utero and during early childhood are more likely to be obese and to suffer from stroke, hypertension, diabetes, and cardiovascular disorder in adulthood. The caveat of this study is that it exploits data on the place of residence during later-life and not place of birth which means it must be assumed that individuals do not move away from their birth place. This is likely to undermine the identification strategy. In addition, the health outcomes in this study are again self-declared. We consider place of birth and not place of residence during later-life to define treatment status which should attenuate problems related to treatment miss-classification.

Schiman et al. (2019) also exploit data at a fine geographical level to study the effects of WWII. However, the focus of this study is different. They do not study the effects of warfare, but rather the war-induced rise in infant mortality in 1940–1941 in England and Wales on self-reported health, income and employment. Conti et al. (2019) examine the effects of warfare on height, weight, BMI, IQ and mental deficiency using city-level data of monthly civilian deaths during the Dutch Hunger Winter. Different from the present study which focuses on early childhood exposure, Conti et al. (2019) focus on prenatal exposure.

In contrast to most of the existing studies which have to rely on self-reported health outcomes we use data on objectively measured health outcomes including cancer, hyper-

tension, angina, myocardial infarction, diabetes and obesity. We thereby avoid potential bias from misreporting. The richness of our data allows us to control for a range of family and individual characteristics including, for example, the socioprofessional categories of the woman and her father, and health-affecting behaviours such as tobacco consumption, sleep duration, and diet. We are able to distinguish the effects of war-related hardship as captured by our measures of war exposure based on the historical data from the effect of war-related nutritional shortages by controlling for the level of hunger suffered during WWII as reported by the participants in our data.

We find evidence for adverse long-run consequences of exposure to WWII on wartime children's health outcomes. Women who have been exposed more intensely to WWII are more likely to suffer from any of the health conditions registered in the data but only if the exposure occurred during the first five years of their life. A 10 percent increase in the number of deaths per 100,000 inhabitants in the postcode area of birth increases the probability of suffering from any of the health problem by 0.08 percentage points for women exposed at ages 0 to 5 relative to older and younger cohorts. This is relative to a mean of 49 percent for the sample as a whole. These results are robust to the inclusion of the registered health-affecting behaviours (tobacco consumption, sleep duration, and diet) which suggests that the effects are not mediated through changes in these health behaviours. We also find some limited evidence for adverse health outcomes among women born in postcode areas which were home to an above average number of POW compared to women from postcode areas with a below average number of POW. However, this result is not very robust and should be interpreted with caution. Using Allied bombing as measure of war exposure did not yield any significant results.

War exposure as measured by the number of military casualties could potentially capture the effect of exposure to stress from experiencing or witnessing battle-related violence or stress related to fleeing the advancing troops. The number of POW could be an indirect measure for the likelihood that the woman has grown up in the absence of a father or other male relative, which could have implied lower household resources and thus worse outcomes in adulthood. Interpreting the measures in this way, the results of this study suggest that it could have been the exposure to violence and, to a lesser extent, the absence of a father or male relative which potentially impacted later-life health outcomes. Our results remain unchanged when we control for the level of hunger suffered during WWII as reported by the participants in E3N, suggesting that the effects we capture through our measures of war exposure are distinct from the effects of war-related nutritional shortages.

Contrary to the effects of war on physical capital, which have been shown to be relatively short-lived (Bellows and Miguel, 2009; Brakman et al., 2004; Davis and Weinstein, 2002; Miguel and Roland, 2011), the results presented in this paper suggest that the effects of war on human capital are long-lasting. Our findings underline the importance of post-conflict policies primarily targeting children exposed during early childhood to mitigate, or potentially reverse, the adverse long-term health effects caused by exposure to war. This is of particular relevance in a world where the number of armed conflicts is at an all-time high (Strand et al., 2019).

# 2. Background and data description

## *2.1. The German invasion of France as exogenous shock: historical background*

We consider the spatial and temporal variation in war exposure related to the German invasion of France during the Battle of France to be a shock that is exogenous to individual and family characteristics. This is not an unreasonable assumption given that the German invasion occurred suddenly and unexpectedly. The battle fronts moved quickly and were not concentrated in areas that the French expected to have to defend. The Battle of France lasted only six weeks (10 May - 25 June 1940). Germany relied on surprise *blitzkrieg* ("lightning war") techniques. Their strategy was to carry out a subsidiary attack through neutral Belgium and the Netherlands, with the main attack against France to be launched a little later through the Ardennes. This was a hilly and forested area on the German-Belgian-French border, where the Allies did not expect an attack. In what follows we briefly summarise the main battle movements.

The German attack began on 10 May 1940, with German air raids on Belgium and the Netherlands, followed by parachute drops and attacks by ground forces. On 14 May the Dutch surrendered. As planned by the Germans, the British and French responded by pushing their forces into Belgium. On 13 May, the first German forces arrived near Sedan, on the River Meuse. With most of the Allied forces fighting in Belgium, the German forces encountered little resistance. They quickly broke the Allied supply-lines and reached the English Channel on 20 May. The German forces then advanced through Belgium and encircled the Allied forces by moving tanks up from the south and west. The Belgian army

surrendered on 28 May. Between 26 May and 4 June, 338,000 Allied troops were evacuated from Dunkirk. On 5 June, the German forces started to move southwards from the River Somme and launched an offensive on Paris on 9 June. Paris was captured on 14 June, a little more than a month after the beginning of the Battle of France. The German troops crossed the River Loire in the west on 17 June and reached the Swiss frontier a few days later. The Battle of France ended with the surrender of France on 22 June (BBC, 2011).

The armistice led to the creation of a new "French state" under *Maréchal* Philippe Pétain governing from Vichy. German troops occupied three-fifths of the French territory, northern France and the Atlantic coast, leaving the south and eastern two-fifths under Vichy's control. The northern departments of the Nord and Pas-de-Calais had direct military control from Brussels, Alsace and Lorraine were reincorporated into the Reich, a forbidden zone was established in north-eastern France, and an Italian zone was created in south-eastern France in November 1942 (Mouré, 2010).

## *2.2. Explanatory framework for causal long-run effects on health of early-life conditions*

The "Developmental Origins of Health and Disease (DOHaD)" hypothesis postulates that risk factors, protective factors, and early-life experiences affect long-term health and disease outcomes. Although exposure to particular environments and experiences appear to influence health development at all stages in life, it has been suggested that exposure to environmental insults during childhood and adolescence has particularly powerful and long-lasting consequences on health due to the persistence of bio-behavioural attributes that are acquired early in life.

The relationship between early life exposure and health trajectories has been explained using both latency and pathway models. The latency model links early-life exposure to adult health outcomes in a direct manner independently of intervening life circumstances. It proposes that early-life exposures can program long-term or permanent changes in biological and behavioural systems (Barker, 1992; Halfon and Hochstein, 2002; Hertzman, 1999). The pathway model proposes that early-life exposure relates to adult health outcomes indirectly through changes in health-affecting behaviours and life conditions. Negative childhood experiences may lead to unhealthy behaviours such as substance abuse and poor school performance in adolescence and limited opportunities in adulthood. Inadequate resources and stressful life circumstances in adulthood, in turn, increase the risk of morbidity and mortality

(see for example Ben-Shlomo and Kuh (2002)). The latency and pathway models are not competing explanations, but are thought to be intertwined in a complex manner. Chronic disease may be the long-term outcome of childhood conditions and experiences combined with cumulative exposures across adulthood (Blackwell et al., 2001).

## *2.3. Data description*

The *Etude Epidémiologique auprès de femmes de la Mutuelle Générale de l'Education Nationale* or E3N is a French prospective cohort study which was initiated in 1990 to investigate the risk factors associated with cancer and other major non-communicable diseases in women. E3N participants were insured through a national health system that primarily covered teachers, and were enrolled in the study from 1990 onward after returning baseline self-administered questionnaires and providing informed consent. The cohort comprised nearly 100,000 women (mainly teachers) born between 1925 and 1950 and therefore aged 40 to 65 years at recruitment. Follow-up questionnaires were sent approximately every 2-3 years and addressed general and lifestyle characteristics together with medical events which include among others cancers, cardiovascular diseases, diabetes, depression, fractures and asthma. Our study includes data from the follow-up questionnaires until 2014. The follow-up questionnaire response rate remained stable at approximately 80% (Clavel-Chapelon, 2014).

The E3N data provide information on a wide range of individual characteristics including the date and place of birth, educational achievement, a measure for the level of stress experienced at work, marital status, information on early childhood conditions such as preterm birth, birth weight and height, physical activity during childhood, age of the mother and father at birth, the woman's, her husband's and father's socioprofessional status, whether the individual lived on a farm, number of siblings and information on the presence of health conditions in the family. Registered health outcomes include occurrence of any cancer, myocardial infarction, angina, diabetes, hypertension and obesity. These health outcomes have been validated using the data from the national health system. We observe a range of health behaviours including tobacco consumption, average sleep duration, and diet in terms of carbohydrate, protein, fat, and total calorie intake. In the first questionnaire, the participants were asked how much they suffered from the hardships of WWII in terms of food deprivation. The possible answers were "not born at the time", "not at all or few suffering", "moderate suffering", "a lot" (continuous hunger), "enormously" (deportation).

Albeit subjective, this variable is interesting as it allows us to distinguish the effect of nutritional shortages from the effect of other war-related hardship. Figure A1 in the Appendix shows a map with the postcode area average of the self-reported level of food deprivation. Individuals seemed to have suffered from hunger all across France and there is no apparent spatial clustering.

We merge the E3N data with data we collected from several historical sources. Our most important source is the database *"Memoire des hommes"* managed by the French Ministry of Armed Forces and available at their website. The data is based on the death records of French soldiers and is said to be exhaustive. We scrape the information on the soldier's place of death and construct a measure of war exposure based on the number of military casualties or the number of military casualties per 100,000 inhabitants at the level of the postcode area. Figure A2 in the Appendix shows a map with the distribution of the French military casualties per 100,000 inhabitants at the level of the postcode area. Unsurprisingly, military deaths appear to be concentrated in the north-east along the path of the German invasion during the Battle of France. Figure A3 shows how the number of French military deaths evolved during the months of the Battle of France in the northern zones which would become the German occupied zone soon after the end of the battle, compared to the southern zone which only fell under German military administration in November 1942. We can see that the number of deaths rises rapidly during the months of May and June 1940 and only in the north of France which coincides with the timing and location of the battles during the Battle of France (see section 2.1 on the historical background).

We construct several other measures of war exposure. We use data from digitised paper mission reports of air warfare between 1939 and 1944 to construct different measures of intensity of the Allied bombing of France: an indicator variable equal to one if any bomb was dropped in a given postcode area, the number of bombs dropped in a given postcode, the distance of any postcode area centroid to the nearest bomb, or the mean distance to any $k$ nearest bombs. Figure A4 shows a map with the exact location of where the bombs were dropped. We further use data on the French prisoners of war from the official lists provided by the German military authority between 1940 and 1941, made available online by the National Library of France. Using optical character recognition software and merging the place of birth of the prisoners with postcodes, we obtain a data set including about 10% of the total population of French prisoners of war. We use the number of prisoners of war original from a given postcode area as a measure of war exposure in terms of the absence of a father or male breadwinner, supposing that children in areas which were home to a larger

number of prisoners of war had a higher probability of having suffered from the absence of a father. Figure A5 shows a map with the number of POW at the level of the postcode area.

For the merging and for the construction of the maps, we use a France shapefile with administrative boundaries at the postcode level. We exclude observations for which we do not have full information on important covariates (lives with a partner, higher education, socioprofessional category of the individual and her father, born preterm, mother's and father's age at birth, number of siblings, physically or mentally stressful job, lived on a farm, lives in deprived area, suffered from hunger during WWII). Our results are robust to using the full data set including fewer covariates. Table A1 in the Appendix presents summary statistics for this final sample.

# 3. Identification strategy

To estimate causal effects of early-life exposure to WWII on later-life health, we exploit variation in the intensity of WWII across time and space, which is plausibly exogenous to individual and family characteristics. More precisely, we compare the health of women born in postcode areas which were intensely affected by the war with the health of women belonging to the same generation but who were born in less affected postcode areas, relative to the health of women from other birth cohorts. Similar approaches to establish causality have been used in the literature (see for example Akbulut-Yuksel (2017); Kesternich et al. (2014); Schiman et al. (2019)). We write our model as follows

$$H_{ipt} = \alpha + \beta_1 Exposure_p + \beta_2 Exposure_p \cdot gen_{it} + \gamma_t + \delta_d + \rho X_{ipt} + \epsilon_{ipt} \tag{3.1}$$

where $H_{ipt}$ denotes the health outcomes for individual $i$ born in postcode area $p$ in year $t$, $Exposure_p$ is the measure of war exposure at the level of the postcode area $p$, $gen_{it}$ is an indicator variable equal to one if individual $i$ born in year $t$ is part of the generations we consider to be treated, and $X_{ipt}$ is a vector of controls for individual and family characteristics. Year of birth and spatial (department level) fixed effects are denoted $\gamma_t$ and $\delta_d$, respectively, and $\epsilon_{ipt}$ is the standard error. Results are robust to clustering at the level of the spatial fixed effects (the department).

War exposure is constructed either based on the number of French military casualties, the number of French prisoners of war original from the postcode area or the intensity of the Allied bombing. The dependent variables are binary as they describe whether an individual

is affected or not by disease. We therefore run Logit regressions and report the estimates of the average marginal effect. The results are qualitatively similar when we use linear probability models.

Including the indicator variable $gen_{it}$ which marks individuals as belonging to the treated generations allows us to compare the effects across groups of birth cohorts. This is useful to investigate whether exposure to the war has heterogeneous effects with respect to age at exposure. Almond and Currie (2011) suggest for example that adverse shocks negatively affect individuals between conception and 5 years of age more intensely than older individuals whereas others such as Sparén et al. (2004) argue that the onset of puberty is a sensitive period as the body collects resources in anticipation of the adolescent growth spurt. Our estimate of interest is the coefficient $\beta_2$ on the interaction term between the exposure to WWII and the variable indicating the individual belongs to the treated generations. This is the differences-in-differences estimate capturing the effect of WWII on health for women who have been exposed intensely relative to women from the same group of birth cohorts but who have been less exposed, and relative to women from other birth cohorts. We test several model specifications in which we consider different groups of birth cohorts to be treated. In our main specification, we consider as treated all individuals born from 1935 to 1939 and thus aged 0 to 5 years at the time of the invasion, while the younger and older birth cohorts serve as the control group.

Our identification strategy relies on the assumption that the geographical measure of exposure is sufficiently correlated with the actual hardship experienced at the level of the individual. This does not have to be the case. Families who are exposed to WWII in a similar way might be able to mitigate the effects of the war on the children more or less well, for example, because they belong to the ruling elite or because the parents differ in altruism or capability. We control for all observable family characteristics, such as for example the father's socioprofessional category which should capture to some extent the parent's capacity to mitigate shocks.

The vector of covariates $X_{ipt}$ includes the individual's marital status, a measure for the level of physical and mental stress experienced by the individual at her work, her educational achievement, indicator variables for the socioprofessional category of the individual and her father, the number of siblings, information on whether the individual was born preterm, whether the individual lived on a farm, and indicators for the existence of cancer, diabetes, and hypertension in the family. Controlling for hunger allows us to distinguish the effect of exposure to the war as captured by our measures of war exposure from nutritional deprivation

as another source of war-related hardship. In some regressions we add controls for the health-affecting behaviours we observe in the E3N data including tobacco consumption, average sleep duration, and diet-related measures such as fat, protein, carbohydrate and total calorie intake.

Finally, the validity of the difference-in-differences estimates relies on the presence of a parallel trend across treatment and control postcode areas. Outcomes in the affected postcode areas should be similar to outcomes in the unaffected areas had there been no exposure to the war. We test if the assumption is plausible by interacting the measure of war exposure with different sets of cohort dummies to check whether the difference in health outcomes for women born in affected versus unaffected postcode areas is significant only for cohorts that could have been exposed. We should only find effects for the generations that were alive at the time of the Battle of France but not for the cohorts born afterwards.

# 4. Results

## *4.1. Effects of war exposure as measured by French military casualties*

Table 1 presents evidence for the plausibility of the parallel trend assumption and reports our main results for the effect of exposure to WWII as measured by the logarithm of French military casualties per 100,000 inhabitants on the probability of suffering from health problems during adulthood (we use log of deaths+1 to avoid missing values for observations with 0 deaths). Column one shows results for the interaction of the measure of war exposure with 5-year birth cohort groups. We find that an increase in the intensity of war exposure affects health outcomes negatively for women born from 1935 to 1939 but not for older and younger cohorts. These women were in between 0 and 5 years old during the Battle of France at the onset of the war when most of the exposure occurred. Figure A6 in the Appendix illustrates this result graphically. Not finding any significant results for the cohorts born after the Battle of France supports the parallel trend assumption. Outcomes for women born in the affected versus the unaffected areas appear no different for the cohorts who did not experience the German invasion. Interestingly, we do not find results for the cohorts born before 1935. These cohorts experienced the Battle of France, albeit at an older age. This suggests that exposure affects in particular young children.

Estimation of our differences-in-differences specification as formalised in Equation (1)

is reported in the second column of Table 1. The dependent variable here is a single binary variable indicating the presence of any health condition, equal to 1 if the individual developed any of the observed health conditions and 0 otherwise. A 10 percent increase in the number of deaths per 100,000 inhabitants in the individual's postcode area of birth increases the probability of suffering from any of the health conditions considered in this study by 0.08 percentage points for the women born from 1935 to 1939 relative to older and younger cohorts. This is significant compared to a mean of 49% for the sample as a whole. We do not find such effects for individuals from other birth cohorts. Considering only the deaths occurring during the Battle of France (both per 100,000 inhabitants or absolute numbers) yields qualitatively similar results. Columns three and four of Table 1 report results for health outcomes on a more disaggregate level. We find that exposure to WWII increases the probability of suffering both from cancer and from "metabolic syndrome" diseases which includes hypertension, angina and diabetes. Cardiovascular diseases and diabetes, as well as obesity, are often grouped under the term "metabolic syndrome" because they are related (associated with lifestyle, e.g. diet and physical exercise habits) and often occur together. Including or excluding myocardial infarction and obesity for the construction of the 'metabolic syndrome" variable does not change the precision of our estimation or the point estimate. Considering hypertension, angina and diabetes separately does not yield statistically significant results.

We found evidence to suggest that our results may be driven by the effects in women exposed at around 2 years of age. Looking at the interaction of exposure with year of birth shows that the effects are only visible for women born in 1938 (and surprisingly not for those born in 1939). See Figure A7 in the Appendix for a graphical representation of this result. However, when we consider smaller cohorts as treatment cohorts (e.g. the 2-year cohort born in 1938-39 or the 3-year cohort born from 1937-39) relative to the younger and older cohorts in the differences-in-differences regressions, we mostly obtain results that are not significant.

Table 1: Effect of early-life exposure to WWII as measured by the number of French military casualties per 100,000 inhabitants on adult health

| | Any health condition | | Cancer | Metabolic diseases |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Exposure x Born 1925-34 | 0.0011 | | | |
| | (0.0035) | | | |
| Exposure x Born 1935-39 | $0.0076^{**}$ | $0.0080^{**}$ | $0.0053^{*}$ | $0.0056^{**}$ |
| | (0.0036) | (0.0038) | (0.0029) | (0.0027) |
| Exposure x Born 1940-45 | $-0.0033$ | | | |
| | (0.0026) | | | |
| Exposure x Born 1946-50 | 0.0013 | | | |
| | (0.0027) | | | |
| Exposure | | $-0.0004$ | $-0.0004$ | $-0.0008$ |
| | | (0.0017) | (0.0013) | (0.0019) |
| Lives with partner | $-0.0054$ | $-0.0055$ | $-0.0019$ | 0.0043 |
| | (0.0085) | (0.0085) | (0.0052) | (0.0077) |
| Higher education | $-0.0405^{***}$ | $-0.0405^{***}$ | 0.0034 | $-0.0519^{***}$ |
| | (0.0055) | (0.0055) | (0.0047) | (0.0055) |
| Born preterm | $0.0426^{**}$ | $0.0425^{**}$ | 0.0109 | $0.0343^{**}$ |
| | (0.0187) | (0.0187) | (0.0098) | (0.0172) |
| Mother's age at birth | $-0.0003$ | $-0.0003$ | $-0.0007$ | 0.0005 |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Father's age at birth | $-0.0006$ | $-0.0006$ | 0.0003 | $-0.0010$ |
| | (0.0008) | (0.0008) | (0.0006) | (0.0006) |
| Nb. of siblings | $-0.0035^{**}$ | $-0.0034^{**}$ | $-0.0011$ | $-0.0024^{*}$ |
| | (0.0014) | (0.0014) | (0.0012) | (0.0013) |
| Physically stressful job | 0.0080 | 0.0080 | $0.0178^{***}$ | 0.0026 |
| | (0.0077) | (0.0077) | (0.0054) | (0.0067) |
| Mentally stressful job | 0.0127 | 0.0128 | $-0.0025$ | $0.0154^{*}$ |
| | (0.0098) | (0.0098) | (0.0054) | (0.0088) |
| Lived on a farm | 0.0046 | 0.0047 | 0.0085 | 0.0019 |
| | (0.0072) | (0.0072) | (0.0054) | (0.0063) |
| Lives in deprived area | 0.0053 | 0.0053 | $-0.0031$ | $0.0088^{***}$ |
| | (0.0036) | (0.0036) | (0.0022) | (0.0033) |
| Hunger (scale) | $0.0340^{***}$ | $0.0340^{***}$ | $0.0144^{**}$ | $0.0233^{***}$ |
| | (0.0064) | (0.0064) | (0.0058) | (0.0066) |
| Bombs | 0.0005 | 0.0006 | 0.0041 | $-0.0005$ |
| | (0.0070) | (0.0070) | (0.0059) | (0.0073) |
| Num. obs. | 28324 | 28324 | 26165 | 28324 |
| Log Likelihood | $-19023.9073$ | $-19024.8850$ | $-11624.4387$ | $-17494.7512$ |

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Exposure is the logarithm of the number of fallen French soldiers per 100,000 inhabitants in the woman's postcode area of birth. All models include birth-year, department fixed effects and dummies for the individual's and her father's socioprofessional category. The coefficients show average marginal effects. Standard errors are clustered at the department level.

The results are robust to the inclusion of the different covariates. We show in Table A2 of the Appendix that the coefficient of interest changes only marginally when we control for a range of individual and family characteristics and remains unchanged when we add further controls for individual life circumstances. The coefficients on the control variables generally have the expected sign. For example, being born pre-term or suffering from hunger during WWII is associated with a higher probability of being sick later in life. This association between WWII-related food deprivation and health outcomes in adulthood is investigated by Mink et al. (2020). Including additional controls for health-related behaviour such as tobacco smoking, sleep duration, physical activity during childhood, and diet still yields similar results.

We further consider the possibility that the effects of war exposure on health manifest only in individuals who have been exposed with an intensity above a certain threshold. We divide individuals into groups according to their quartile of exposure and interact the exposure quartile indicator with the indicator marking whether the individual belongs to the affected generations born from 1935 to 1939. The first quartile includes postcodes areas with less than 14 deaths per 100,000 inhabitants, in the second quartile this number ranges from 15 to 67 and in the third quartile from 68 to 231, while the most exposed fourth quartile includes postcode areas with 232 or more deaths per 100,000. We find that result appear to be driven by the adverse health outcomes faced by women who were born in the most intensely exposed areas. As shown in Table 2, having been born in one of the 25 percent most affected postcode areas relative to the 25 percent least affected postcode areas raises the probability of suffering from any health condition by 4.9 percentage points, for women exposed at ages 0 to 5 relative to the other cohorts.

## *4.2. Other measures of war exposure*

We find some evidence for adverse health outcomes among women born in postcode areas which were home to an above average number of POW compared to women from postcode areas with a below average number. The results are reported in Table A3 of the Appendix. However, this effect only manifests when we use cut-off values, here a cut-off at the average number of POW. Using the absolute number of POW or the number of POW per 100,000 inhabitants does not yield any results. The number of POW could be too imprecise a measure of exposure to war hardship which could explain the absence of more robust effects. We discuss this in more detail in the next section. We do not find any effects when we use Allied bombing as measure of war exposure, despite our best efforts to construct several distinct measures of exposure. The absence of effects could potentially be due to measurement error. The Allied bombing happened during an extended period (1940-1945) and the bombing was strategical, aiming industrial and transport targets which makes it possible that individuals avoided areas that were likely to be bombed.

Table 2: Effect of exposure to WWII on health, any health condition - Heterogeneity with respect to intensity of exposure

| | Any health condition |
|---|---|
| Second quartile exposure x Born 1935-39 | 0.0201 |
| | (0.0190) |
| Third quartile exposure x Born 1935-39 | 0.0306 |
| | (0.0212) |
| Fourth quartile exposure x Born 1935-39 | 0.0492** |
| | (0.0194) |
| Second quartile exposure | −0.0014 |
| | (0.0084) |
| Third quartile exposure | 0.0012 |
| | (0.0094) |
| Fourth quartile exposure | −0.0007 |
| | (0.0092) |
| Num. obs. | 28324 |
| Log Likelihood | −19024.2468 |

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Women are divided into quartiles according to the intensity of exposure (number of fallen soldier) in their postcode area of birth. First quartile from zero to 14 deaths; second quartile from 15 to 67 deaths; third quartile from 68 to 231 deaths; fourth quartile from 232 deaths or more. The omitted category is the first quartile. The model includes birth-year and department fixed effects and the full range of individual and family characteristics with the exception of health related behaviors. The coefficients show average marginal effects. Standard errors are clustered at the department level.

# 5. Conclusion and discussion

This study provides causal evidence of the long-run consequences of war on health outcomes. We find that an increase in the intensity of exposure to WWII as measured by the number of French military casualties leads to worse health outcomes in adulthood for individuals who were 0 to 5 years old at the time of the exposure. Our findings are consistent with evidence from the literature suggesting that exposure to WWII-related hardship has important negative consequences on the health of survivors (for example Akbulut-Yuksel (2017); Havari and Peracchi (2017); Kesternich et al. (2014)). Finding effects only for individuals who were exposed during the first 5 years of their life suggests that there exists a critical or sensitive period of development during which individuals are more vulnerable to adverse experiences. This is in line with results from the literature (see for example Almond and Currie (2011); Cunha and Heckman (2007)).

In contrast to the effects of war on physical capital, which have been shown to be relatively short-lived (Bellows and Miguel, 2009; Brakman et al., 2004; Davis and Weinstein, 2002; Miguel and Roland, 2011), the results presented in this paper suggest that the effects of war on human capital are long-lasting. Our findings underline the importance of post-conflict policies primarily targeting children exposed during early childhood to mitigate, or potentially reverse, the adverse long-term health effects caused by exposure to war.

### *Potential channels and pathways*

Our results are robust to controlling for all of the observed health-related behaviour (tobacco smoking, sleep duration, physical activity, diet) and the level of hunger suffered during WWII as reported by the study participants. This suggests that the effects that we capture through our measures of war exposure are distinct from the effects of war-related nutritional shortages and that the effects are not entirely mediated through changes in the observed health-related behaviours. However, we cannot exclude that there are other unobserved mediating factors or other aspects of the war that affect health outcomes. We therefore cannot conclude that our results are evidence for a direct link between early-life exposure and adult health or if early-life exposure relates to adult health outcomes indirectly through changes in health-affecting behaviours and life conditions (see also the discussion in section 2.2).

Our measures of war exposure are too imprecise to allow the identification of a precise channel through which exposure to the war affects later-life health outcomes. We can only make some attempts at interpretation. We obtain our main results using the number of French military casualties as a measure of exposure to the war. This measure could potentially capture the effect of stress from experiencing or witnessing battle-related violence or stress related to fleeing the advancing German troops. We also find some limited evidence for adverse health outcomes among women born in postcode areas which were home to an

above average number of POW compared to women from postcode areas with a below average number of POW. The number of POW could be interpreted as an indirect measure for the likelihood of growing up in the absence of a father or other male relative, which could imply psychological distress and/or lower household resources and thus worse outcomes in adulthood. However, the results for this measure are not very robust. The effect manifests only when we use cut-off values but not when we use the absolute number of POW. The number of POW could be too imprecise a measure of exposure to war hardship. A higher number of POW could have only a modest impact on the probability of growing up without a father or male relative. This increased probability must then lead to sufficiently large adverse effects on mental or material well-being to induce discernible effects on later-life health.

If we interpret the different measures of exposure as described above, the results of this study suggest that it could have been the exposure to the violence during the Battle of France and, to a lesser extent, the absence of a father or male relative which impacted later-life health outcomes.

### *Sample representativeness, selective mortality and selective fertility*

Our sample is not representative of the general French population. Composed of women enrolled in a national health insurance system which primarily covered teachers, the women in our sample are on average more educated. These women may come from a relatively more privileged background, which may have mitigated their exposure to the war and its effects. Women who were so intensely affected by the war that they were not able to get the necessary education to become employed in the French national education are altogether excluded from our sample. We therefore consider our estimates to be a lower bound for the effects of exposure in the general population.

In addition, there may have been a change in the composition of the population caused by differential mortality. If the least healthy have been more likely to die, the pool of survivors could on average be healthier. In case of such selective mortality, the average health of a population intensely affected by the war would be better than the average health of a less affected population, leading us to underestimate the impact of war on health. This would mean that our estimates are a lower bound for the true effects.

The outbreak of the war is also likely to have affected fertility. The cohorts conceived before 1940 should be unaffected which means that the results showing worse health outcomes for women born in the affected versus unaffected postcode areas for the cohorts 1935 to 1939 but not for the cohorts born before 1935 (Table 1, Column one) should not be subject to bias from selective fertility. However, the composition of the cohorts born at the end of 1940 or later could have been affected. For this to impact our results, there would need to exist differences in fertility not only across cohorts but also across the affected and unaffected postcode areas. We do not find worse health outcomes for women born in the affected relative to the unaffected postcode areas for the generations born after the war. If anything,

a potentially different fertility pattern across postcodes would have resulted in a population that is healthier on average in the affected areas relative to the unaffected areas in a way to offset the negative health effects.

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Table A1: Summary statistics

| | mean | sd | min | max | N |
|---|---|---|---|---|---|
| Health outcomes | | | | | |
| Cancer | 0.17 | 0.37 | 0 | 1 | 28666 |
| Myocardial infarction | 0.01 | 0.1 | 0 | 1 | 28666 |
| Diabetes | 0.05 | 0.23 | 0 | 1 | 28666 |
| Angina | 0.02 | 0.14 | 0 | 1 | 28666 |
| Hypertension | 0.35 | 0.48 | 0 | 1 | 28666 |
| Obesity | 0.02 | 0.15 | 0 | 1 | 28666 |
| Any health condition | 0.49 | 0.5 | 0 | 1 | 28666 |
| Health behaviors | | | | | |
| Sports during childhood | 42.67 | 25.92 | 0 | 215.3 | 28447 |
| Hours of sleep | 7.59 | 1.09 | 4 | 15 | 25600 |
| Tobacco usage | 0.33 | 0.47 | 0 | 1 | 28641 |
| Carb. intake | 234.2 | 73.22 | 12.46 | 1051.35 | 28666 |
| Protein intake | 93.14 | 25.59 | 4.74 | 391.03 | 28666 |
| Lipids intake | 89.8 | 26.97 | 4.52 | 250.69 | 28666 |
| Calorie intake | 2193.93 | 561.47 | 110.94 | 6341.53 | 28666 |
| Takes the pill | 0.59 | 0.49 | 0 | 1 | 28666 |
| Preventive behaviour | 0.4 | 0.25 | 0 | 1 | 28666 |
| Takes hormones | 0.22 | 0.41 | 0 | 1 | 28666 |
| Treatment variables | | | | | |
| Deaths per postcode 1940-45 | 98.07 | 260.31 | 0 | 1853 | 28666 |
| Deaths per 100,000 | 220.9 | 487.7 | 0 | 9947.64 | 28324 |
| Log(1+deaths per 100,000) | 3.89 | 2.07 | 0 | 9.21 | 28324 |
| Covariates | | | | | |
| Year of birth | 1941.3 | 6.47 | 1925 | 1950 | 28666 |
| Lives with partner | 0.85 | 0.36 | 0 | 1 | 28666 |
| Higher education | 0.38 | 0.49 | 0 | 1 | 28666 |
| Born preterm | 0.03 | 0.18 | 0 | 1 | 28666 |
| Number of siblings | 2.14 | 1.87 | 0 | 22 | 28666 |
| Age of mother at birth | 28.23 | 5.65 | 13 | 57 | 28666 |
| Age of father at birth | 31.38 | 6.37 | 13 | 93 | 28666 |
| Lived on a farm | 0.22 | 0.42 | 0 | 1 | 28666 |
| Population density birth city | 3859.01 | 7502.34 | 1.46 | 46529.85 | 28324 |
| Physically stressful job | 0.23 | 0.42 | 0 | 1 | 28666 |
| Mentally stressful job | 0.86 | 0.35 | 0 | 1 | 28666 |
| Deprivation index | -0.25 | 1.02 | -4.11 | 2.67 | 28666 |
| Relative had cancer | 0.78 | 0.41 | 0 | 1 | 26482 |

Continued on next page

Table A1: Summary statistics

| | mean | sd | min | max | N |
|---|---|---|---|---|---|
| Relative had diabetes | 0.12 | 0.32 | 0 | 1 | 28666 |
| Relative had hypertension | 0.37 | 0.48 | 0 | 1 | 28666 |
| Relative had infarct | 0.21 | 0.41 | 0 | 1 | 28666 |
| Woman of high SES | 0.13 | 0.33 | 0 | 1 | 28666 |
| Woman of middle SES | 0.86 | 0.35 | 0 | 1 | 28666 |
| Woman of low SES | 0.02 | 0.13 | 0 | 1 | 28666 |
| Father of high SES | 0.22 | 0.41 | 0 | 1 | 28666 |
| Father of middle SES | 0.6 | 0.49 | 0 | 1 | 28666 |
| Father of low SES | 0.18 | 0.38 | 0 | 1 | 28666 |
| Hunger (scale 1-5) | 1.76 | 0.78 | 1 | 5 | 28666 |
| Bombing in postcode | 0.25 | 0.43 | 0 | 1 | 28666 |
| Infant mortality 36-47 | 3.4 | 0.85 | 1.25 | 5 | 28666 |

Table A2: Effect of early-life exposure to WWII as measured by the number of French military casualties per 100,000 inhabitants in the individual's area of birth on adult health - Robustness to different model specifications

| | Any health condition | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Exposure x Born 1935-39 | 0.0088** | 0.0083** | 0.0083** | 0.0076* |
| | (0.0037) | (0.0037) | (0.0037) | (0.0039) |
| Exposure | −0.0011 | −0.0004 | −0.0005 | 0.0007 |
| | (0.0018) | (0.0018) | (0.0018) | (0.0020) |
| Lives with partner | | −0.0062 | −0.0057 | −0.0056 |
| | | (0.0085) | (0.0086) | (0.0092) |
| Higher education | | −0.0448*** | −0.0421*** | −0.0508*** |
| | | (0.0066) | (0.0067) | (0.0072) |
| Born preterm | | 0.0460*** | 0.0443*** | 0.0300* |
| | | (0.0167) | (0.0167) | (0.0179) |
| Mother's age at birth | | −0.0003 | −0.0004 | −0.0007 |
| | | (0.0008) | (0.0008) | (0.0009) |
| Father's age at birth | | −0.0006 | −0.0006 | −0.0004 |
| | | (0.0007) | (0.0007) | (0.0008) |
| Nb. of siblings | | −0.0034** | −0.0036** | −0.0022 |
| | | (0.0017) | (0.0017) | (0.0018) |
| Physically stressful job | | | 0.0084 | 0.0124 |
| | | | (0.0074) | (0.0079) |
| Mentally stressful job | | | 0.0134 | 0.0105 |
| | | | (0.0090) | (0.0096) |
| Lived on a farm | | | 0.0049 | 0.0023 |
| | | | (0.0077) | (0.0082) |
| Lives in deprived area | | | 0.0055* | 0.0051 |
| | | | (0.0032) | (0.0034) |
| Hunger (scale) | | | 0.0355*** | 0.0372*** |
| | | | (0.0076) | (0.0081) |
| Bombs | | | 0.0006 | −0.0040 |
| | | | (0.0083) | (0.0088) |
| Health behaviours | No | No | No | Yes |
| Num. obs. | 28324 | 28324 | 28324 | 25089 |
| Log Likelihood | -19080.2047 | -19040.3675 | -19023.8850 | -16800.1374 |

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Exposure is the logarithm of the number of fallen French soldiers per 100,000 inhabitants in the woman's postcode area of birth. All models include birth-year and department fixed effects and dummies for the woman's and her father's socioprofessional category. Health-related behaviors are the hours of physical activity in a typical week during childhood, smoking status, the average number of hours slept per night, measures for diet including carbohydrate, protein, lipids, and total calorie intake. The coefficients show average marginal effects. Standard errors are clustered at the department level.

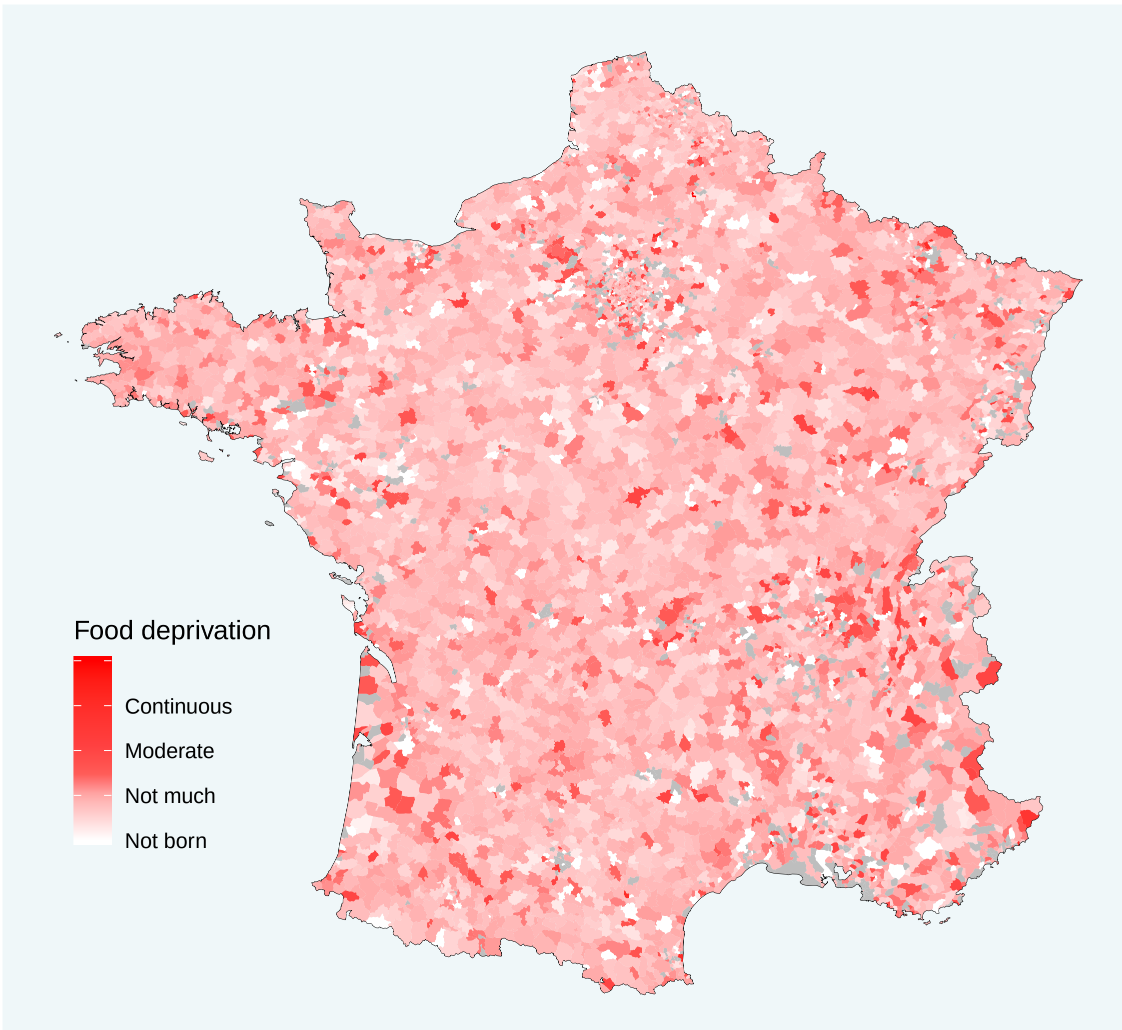


Figure A1.Post-code area average of self-reported level of food deprivation. *Source:* Own work.

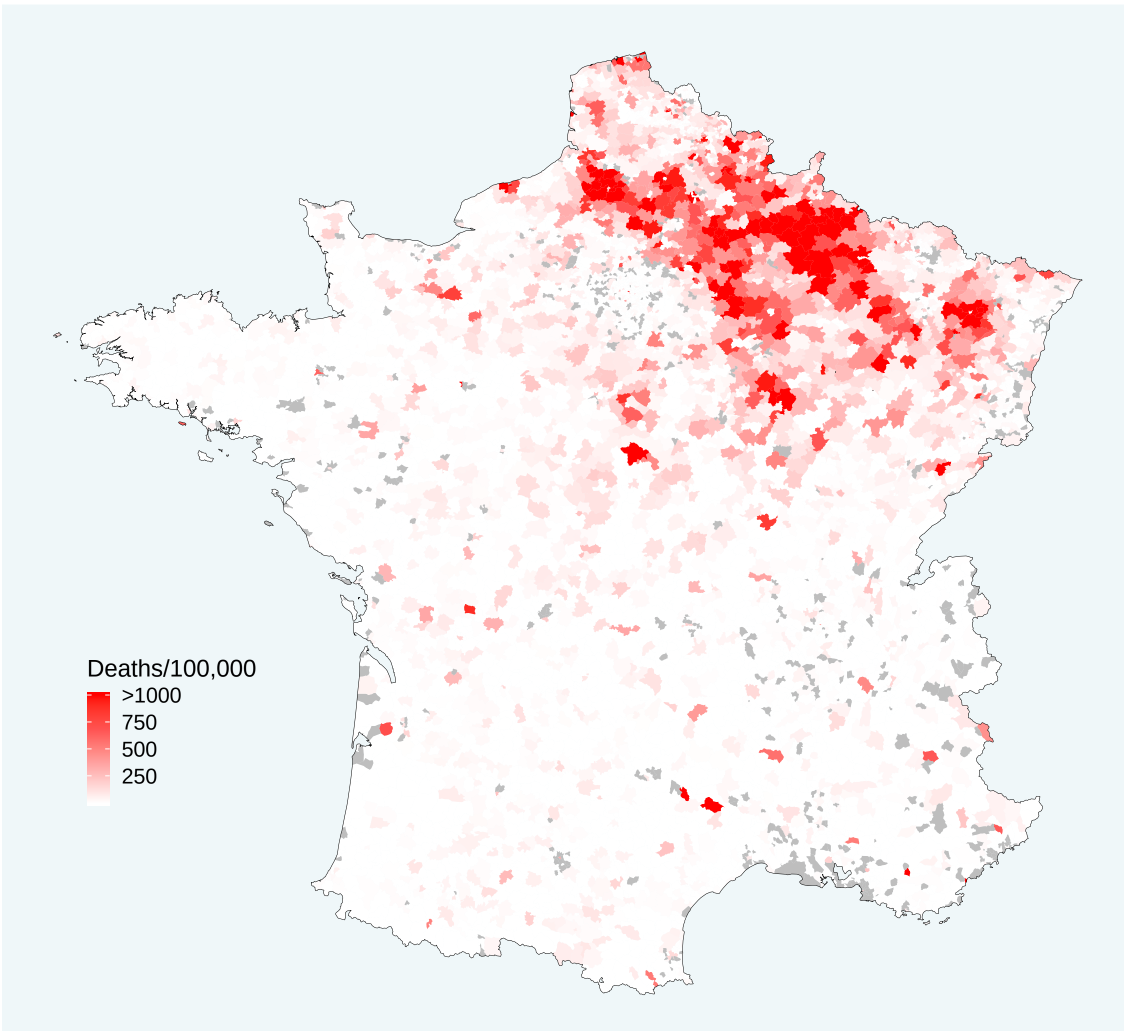


Figure A2.Number of French military deaths per 100,000 at the postcode level, 1940. *Source:* Own work.

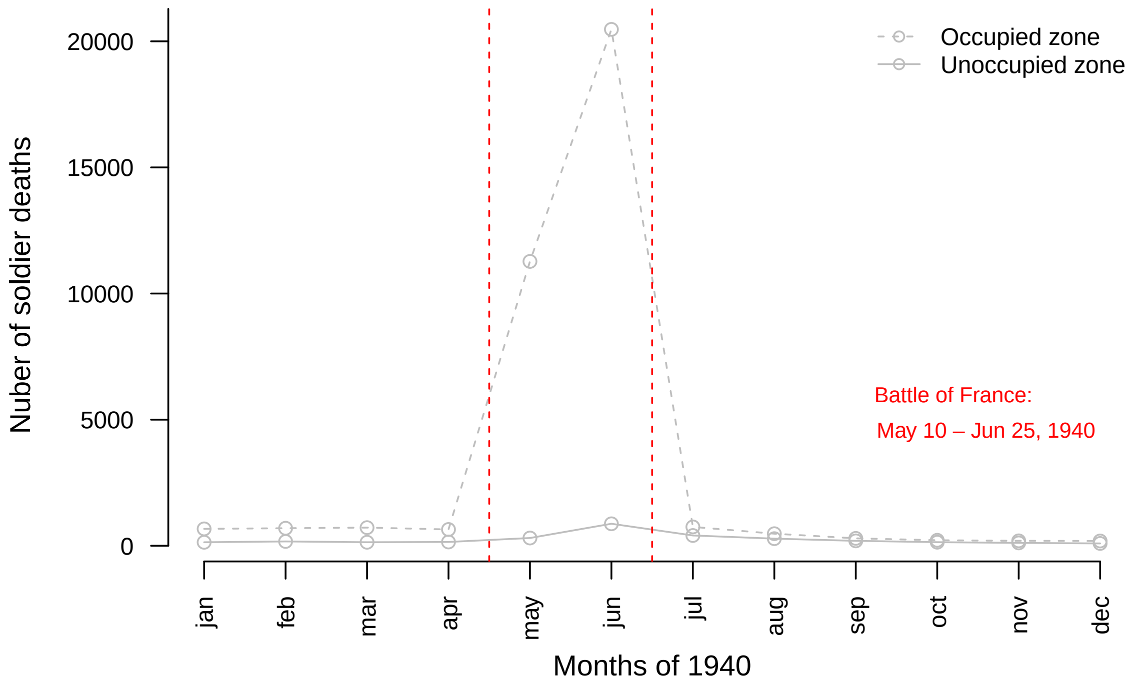


Figure A3.Time-line of the number of deaths of French soldiers, North occupied zones versus South unoccupied zone. *Source:* Own work.

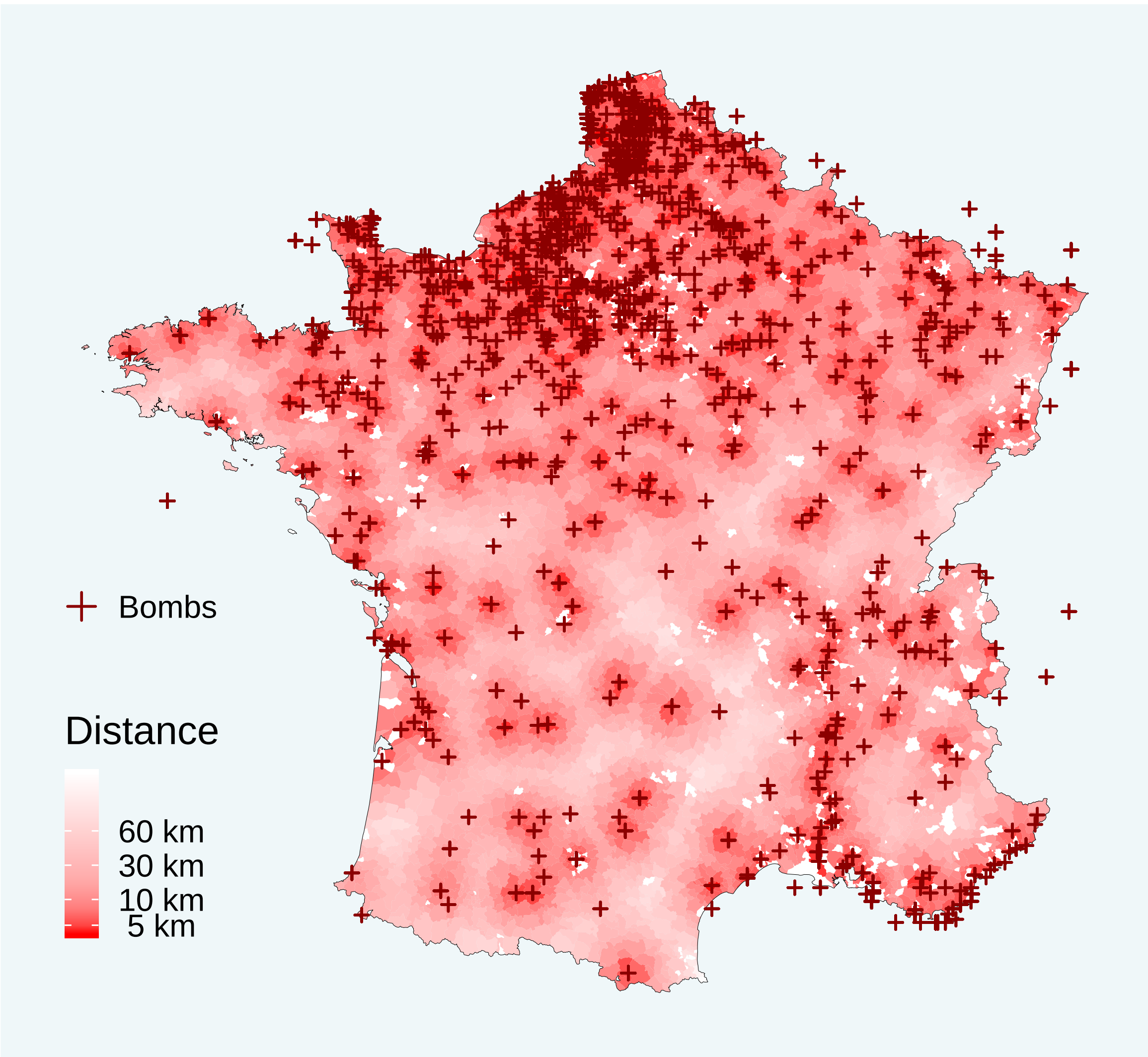


Figure A4.Allied bombing. *Source:* Own work.

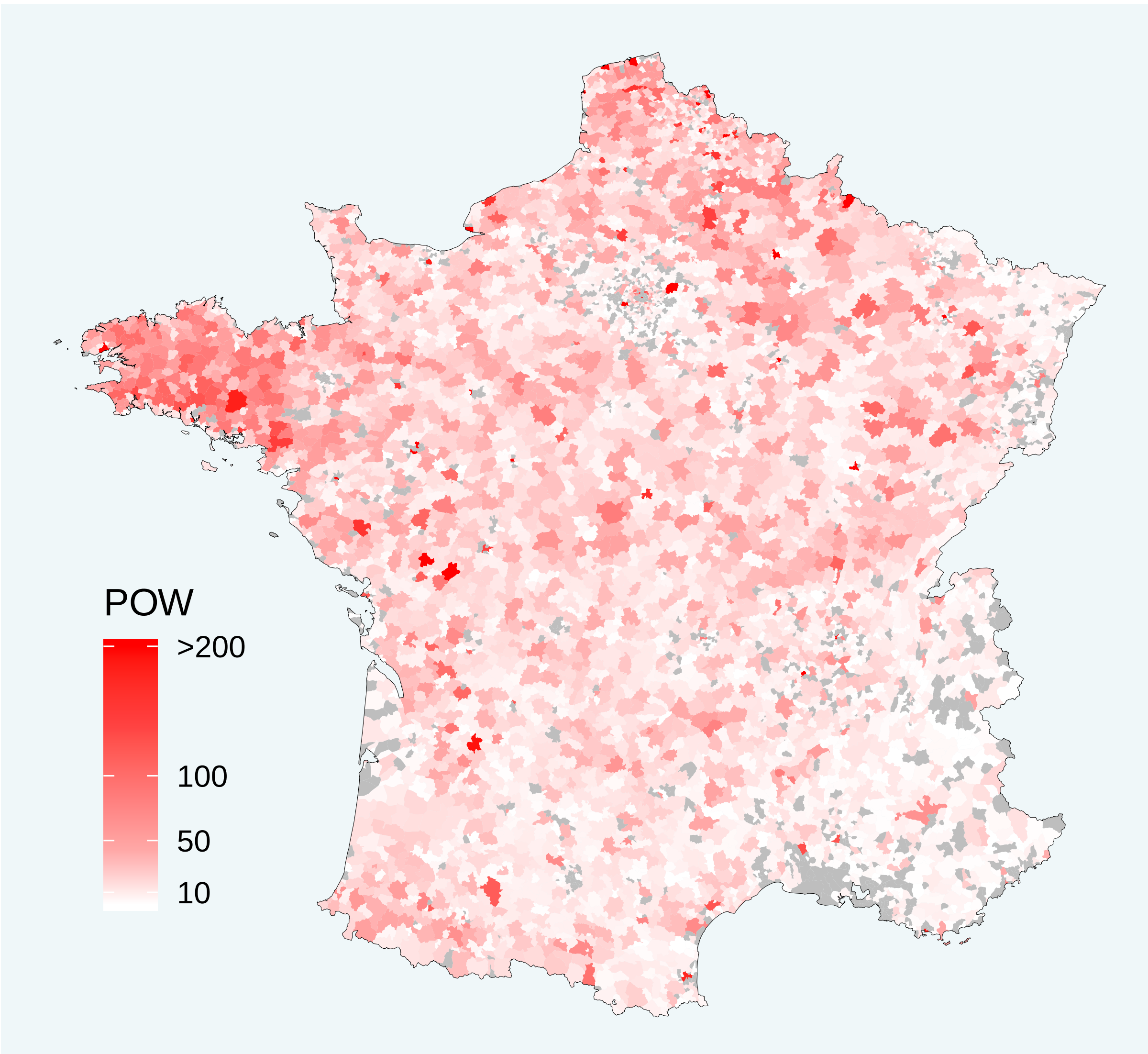


Figure A5.Origin of prisoners of war. *Source:* Own work.

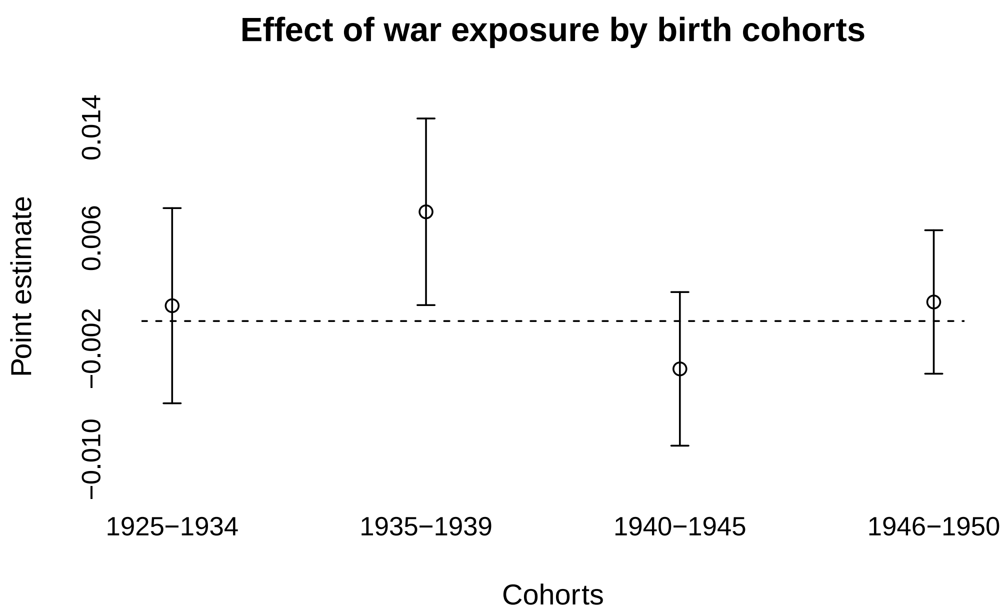


Figure A6.Effect of exposure to war as measured by the number of French military casualties in the individual's postcode area of birth on the probability of suffering from any of the reported health conditions in adulthood. Point estimates by birth cohort. Brackets show 95% confidence intervals.

Table A3: Effect of early-life exposure to WWII as measured by above average number of POW on adult health

| | Any health condition | |
|---|---|---|
| | (1) | (2) |
| Exposure x Born 1925-34 | 0.0001 | |
| | (0.0234) | |
| Exposure x Born 1935-39 | 0.0540** | 0.0382* |
| | (0.0220) | (0.0229) |
| Exposure x Born 1940-45 | 0.0129 | |
| | (0.0187) | |
| Exposure x Born 1946-50 | 0.0256 | |
| | (0.0169) | |
| Exposure | | 0.0159 |
| | | (0.0127) |
| Lives with partner | −0.0064 | −0.0063 |
| | (0.0097) | (0.0097) |
| Higher education | −0.0428*** | −0.0429*** |
| | (0.0076) | (0.0076) |
| Born preterm | 0.0510*** | 0.0511*** |
| | (0.0188) | (0.0188) |
| Mother's age at birth | −0.0006 | −0.0006 |
| | (0.0009) | (0.0009) |
| Father's age at birth | −0.0002 | −0.0002 |
| | (0.0008) | (0.0008) |
| Nb. of siblings | −0.0040** | −0.0040** |
| | (0.0018) | (0.0018) |
| Physically stressful job | 0.0097 | 0.0098 |
| | (0.0083) | (0.0083) |
| Mentally stressful job | 0.0165 | 0.0164 |
| | (0.0101) | (0.0101) |
| Lived on a farm | 0.0004 | 0.0004 |
| | (0.0083) | (0.0083) |
| Lives in deprived area | 0.0073** | 0.0074** |
| | (0.0037) | (0.0037) |
| Hunger (scale) | 0.0389*** | 0.0385*** |
| | (0.0086) | (0.0085) |
| Bombs | −0.0037 | −0.0038 |
| | (0.0093) | (0.0093) |
| Num. obs. | 22662 | 22662 |
| Log Likelihood | -15191.1931 | -15191.6729 |

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Exposure is defined as above average number of prisoners of war in the woman's post code area of birth. All models include birth-year and department fixed effects and dummies for the woman's and her father's socioprofessional category. The coefficients show average marginal effects. Standard errors are clustered at the department level.

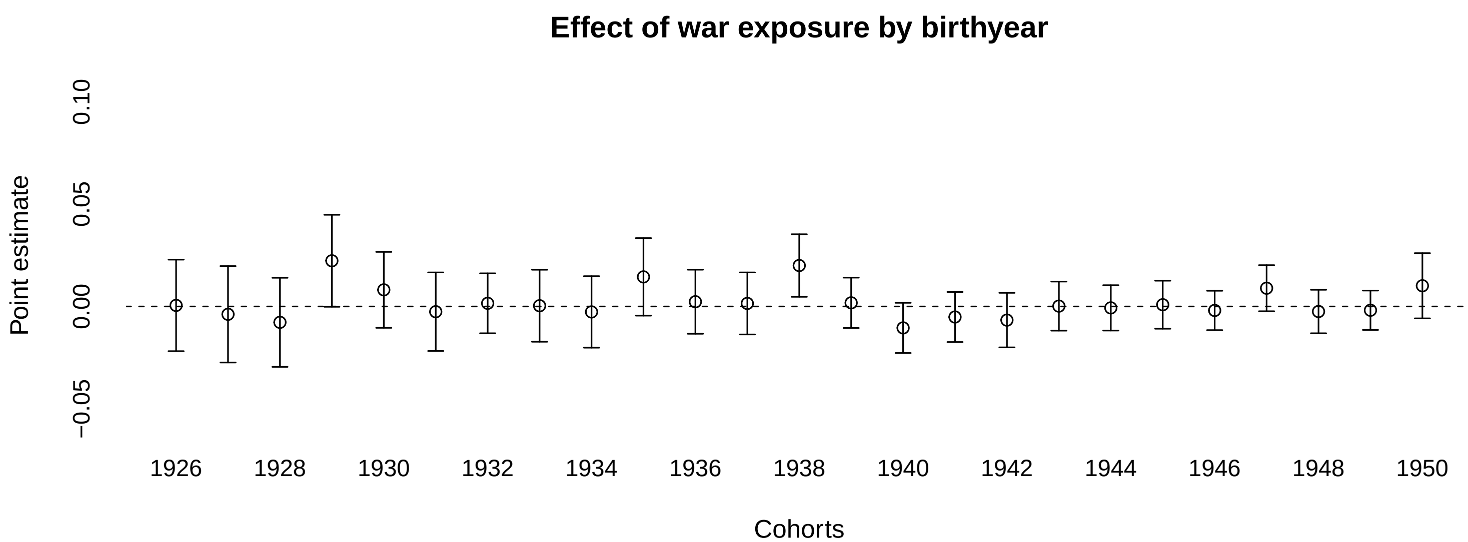


Figure A7.Effect of exposure to war as measured by the number of French military casualties in the individual's postcode area of birth on the probability of suffering from any of the reported health conditions in adulthood. Point estimates by birth-year. Brackets show 95% confidence intervals.

# Chapter 4

# Putting a price tag on air pollution: the social health care costs of air pollution in France

**Abstract**

I estimate the effects of air pollution on health care use and costs using administrative data on health care reimbursements in France and reanalysis data on concentrations of nitrogen dioxide (NO2), ozone (O3) and fine particles pollution (PM 10 and PM 2.5). To establish a causal relationship, I exploit daily variation in air pollution intensity induced by variations in wind speed, wind direction and periods of strikes in the public transport sector. I estimate that each 1 $\mu g/m^3$ increases in daily NO2 (7.2% of the average) results in an increase of €7.57 in daily health expenditure per postcode area, while each 1 $\mu g/m^3$ increase in daily O3 (1.8% of the average) results in an increase of €3.94, which corresponds respectively to a 1.5% and 0.8% increase in average daily expenditure. Summing across postcode areas and scaling the effects appropriately, this translates into an increase in health expenditure of €6.8 million per day or €2.5 billion per year. These costs are the result of exposure to pollution levels that are mostly well below the current regulatory levels. In addition, the estimates reflect only the costs of short-term exposure to air pollution while the potentially even larger effects of long-term exposure are not considered. These high costs from short-term exposure alone suggest that there are considerable benefits to reducing air pollution even further below current limit values. Finally, I find significant heterogeneity of effects across location and patient characteristics, indicating that air pollution reduction policies have the potential to reduce health inequalities.

# 1. Introduction

Exposure to air pollution has well-documented adverse effects on human health such as increased risk of cardiovascular and respiratory disease and cancer. In 2016, air pollution was estimated to contribute to 7.6% of worldwide deaths (WHO, 2017). In response, many countries have put in place air quality standards and objectives for a number of pollutants present in the air. Yet, it is often argued that these standards are set arbitrarily, without conclusive evidence of health benefits to be weighed against the costs of pollution reduction to producers and consumers. Accurate information on the benefits of reducing air pollution is critical in determining the optimal level of environmental policy, particularly in cases where pollution levels are already relatively low and further pollution reductions are likely to be costly. In this study, I estimate the causal effects of air pollution on health care use and costs in France, where pollution levels are on average below the current limit values.

Estimating the causal effect of air pollution on health care costs is difficult due to problems of endogeneity and a general lack of adequate data. People sort spatially according to preferences and characteristics which may be correlated both with their health status and their level of pollution exposure. Families with higher incomes or preferences for cleaner air are likely to sort in locations with lower air pollution (Chay and Greenstone, 2003; Chen et al., 2018). Alternatively, individuals with a high level of education and income may choose to live in urban areas where levels of pollution are on average higher. Failure to consider such non-random exposure results in biased estimates of the effects of pollution on health and health care costs. Without information on incomes or preferences, many researchers have relied on quasi-experimental designs that use a plausible exogenous source of pollution variation to estimate the causal effects of air pollution on health. However, these studies are usually limited to relatively narrow geographical areas and time periods, consider only a specific part of the population or study the effects of pollution on a limited selection of health conditions. Much of this work considers avoided mortality costs. This is a rather extreme event that is less likely to occur following exposure to moderate levels of pollution.

In this study, I investigate the causal short-term effects of exposure to nitrogen dioxide (NO2), ground-level ozone (O3) and fine particles pollution (PM 10 and PM 2.5) on health and health care costs in a representative sample of the French population. I combine unique administrative data on daily health care reimbursements from 2015 to 2018 for all types of health care with exceptionally fine-grained reanalysis data on daily pollution levels and meteorological conditions, and hand-collected data on public transport strikes. I adopt an

instrumental variable (IV) approach where I use as IVs the daily variation in the intensity of air pollution at the postcode area level induced by variation in wind speed, wind direction and periods of strike in the public transport sector. The identifying assumption is that variation in pollution due to changes in wind speed, wind direction or public transport strikes is unrelated to changes in health care use or costs except through the influence on air pollution. This should be the case after flexibly controlling for various time and location fixed effects and several additional covariates such as climatic conditions. Wind direction and common levels of wind speed are unlikely to have a direct effect on health care use other than through the effect on air pollution and I do not find evidence for increased health care use on days of high wind speed. Concerning public sector strikes, the exclusion restriction should hold at least for some selected medical specialties such as cardio-vascular and respiratory care which I can analyse separately from other medical specialties that could be affected by the occurrence of strikes, such as for example trauma surgery due to changes in road traffic accidents, or specialties that are likely to be unresponsive, such as plastic surgery, and serve as placebo.

I find that each 1 µg/m3 increase in daily NO2 (7.2% of the mean) cause an increase of €7.57 in aggregate health care spending whereas each each 1 µg/m3 in daily O3 (1.8% of the mean) causes an increase of €3.94 which corresponds to an increase of 1.5% and 0.8% relative to the average daily spending. Using strikes as instrument rather than wind speed yields even larger estimates. These estimates reflect the costs of acute (short-term) exposure to air pollution, without considering the potentially greater effects of long-term exposure. Yet, the costs of short-term exposure alone suggest that there are considerable benefits to reducing air pollution. Summing across postcode areas and scaling the effect to the size of the entire French population, this translates into an increase in health expenditure of €6.8 million per day or €2.5 billion per year. To put this into perspective, the cost of complying with the National Emission Commitment (NEC) Directive (2016/2284/EU)[1] for France has been estimated to be €9.9 billion per year (Amann et al., 2017). According to my estimates, the further reduction in NO2 pollution levels required to meet the NEC goal results in an annual saving of €5.2 billion in healthcare costs per year. The benefits from a reduction in short-term health care costs due to the decreased NO2 pollution alone (disregarding the changes in other pollutant levels and effects on mortality or productivity, natural systems, etc.) sets off 40% of the total costs of compliance with the NEC directive.

[1]Directive (EU) 2016/2284 of the European Parliament and of the Council of 14 December 2016 on the reduction of national emissions of certain atmospheric pollutants, amending Directive 2003/35/EC and repealing Directive 2001/81, `https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016L2284&from=EN`

I further find significant heterogeneity in effects across patient characteristics and postcode areas. The increase in health expenditure for an increase in daily NO2 or O3 is 4-6 times higher in the most unequal postcode areas (postcode Gini Index is in the highest quintile) compared to the most equal postcode areas (postcodes Gini Index is in the first quintile). The effects are 1.4 to 2.1 times stronger in the postcode area with the highest quintile of unemployment rate compared to the postcode area with the lowest quintile of unemployment rate. Yet, the effect relative to the mean is similar between the first and last quintiles because of the higher average health care spending in the postcode areas with the highest Gini Index or highest unemployment rates compared to the areas with the lowest Gini Index or unemployment rates. While most studies find adverse health effects among the youngest and elderly population, I find evidence of effects across all age categories. The estimated level effect is higher for individuals 40 years and older, but the effect relative to average age group expenditures is more similar across age groups. This could be because most studies find stronger effects in the young and elderly with respect to mortality, which is a rather extreme event likely to affect only the most vulnerable, whereas I am looking at health care costs that include the costs of treating milder health effects that appear to manifest across all age groups.

This study contributes to the recent quasi-experimental literature on the health effects of air pollution. The idea of exploiting public transport sector strikes or meteorological conditions to estimate the causal effects or air pollution on health is not new. In a working paper, Giaccherini et al. (2019) exploit public transportation strikes as exogenous shocks to pollution. However, the scope of this work is much smaller than the present study as it focuses on the effects of particulate pollution on hospital admissions and costs in 111 Italian municipalities. Similar studies that also use data on pollution and public sector strikes are Godzinski and Suarez Castillo (2019) investigate the impact of public transport strikes on hospital admissions for influenza, gastroenteritis and respiratory diseases in the 10 major cities in France and Bauernschuster et al. (2017) investigate the impact of strikes on hospital admissions for respiratory disease in a selection of German cities. Again, the scope these studies is much smaller. In addition, the objective of these studies differs as the authors study the impact of strikes on health rather than the impact of strike-induced pollution. An example of a paper using meteorological conditions is Deryugina et al. (2019) which estimates the causal effects of acute fine particulate matter exposure on mortality, health care use, and medical costs by instrumenting for air pollution using changes in local wind direction. However, Deryugina et al. (2019) is limited to studying the population of the US elderly as they employ Medicare data. In fact, most of the existing quasi-experimental

studies focus on a relatively narrow geographic area or on events that are limited in time, often consider only a specific part of the population and/or investigate the effects of pollution on a limited selection of health conditions (Ransom and Iii, 1995; Pope III and Dockery, 1999; Friedman et al., 2001; Chay and Greenstone, 2003; Neidell, 2004; Currie and Neidell, 2005; Jayachandran, 2009; Neidell, 2009; Moretti and Neidell, 2011; Currie and Walker, 2011; Chen et al., 2013; Anderson, 2015; Schlenker and Walker, 2015; Knittel et al., 2016; Arceo et al., 2016; Deryugina et al., 2016; Schwartz et al., 2016; Ebenstein et al., 2016; Deschênes et al., 2017; Deryugina et al., 2019; Simeonova et al., 2019). Much of this work considers avoided mortality costs. This is a rather extreme event that is less likely to occur following exposure to moderate levels of pollution. Total health care costs related to the treatment of conditions that are caused or aggravated by air pollution are generally not quantified directly as detailed information on total health care expenditure is rarely available.

I estimate health care expenditure more accurately and comprehensively than has been done before. To the best of my knowledge, this is the first quasi-experimental study to comprehensively quantify the health care costs caused by exposure to moderate levels of air pollution in a nationwide representative sample. I also explore treatment effect heterogeneity both by location and patient characteristics in greater depth than previous studies. Using variation in pollution levels across a broad geographic scale enables me to rigorously explore treatment effect heterogeneity by location characteristics such as average income, unemployment rates, and income inequality. Observed patient characteristics include age, sex and chronic health condition.

This study also contributes to the literature on measuring the health costs of air pollution for cost-benefit analysis to inform policy making. Most studies that seek to evaluate the health costs of air pollution for cost-benefit analysis estimate the costs indirectly through simulations based on air quality and population data, baseline rates of mortality and morbidity, concentration-response parameters from the epidemiological literature, and unit economic values. Often, only a selection of health effects for which epidemiological evidence is most robust are included in these models. I am not aware of any study that comprehensively quantifies health care costs in France. A 2007 impact study on the costs to health insurance that was conducted by the French Agency for Environmental and Occupational Health Safety (Fontaine et al., 2007) considered only asthma and cancer as sufficient health and economic data were not available for all air pollution-related diseases. The estimate of the overall cost of asthma and cancer treatments attributable to air pollution was situated between 0.3 and 1.3 billion euros which is extremely small compared to my estimate of €2.5 billion for a 1 $\mu g/m^3$ change in air pollution concentrations. Another study carried out by

the General Commission for Sustainable Development in 2015 sought to assess as comprehensively as possible the cost of air pollution to the French health care system (Rafenberg, 2015). However, the study only covers a selection of disease categories (cost of treatment of respiratory diseases (asthma, acute bronchitis, chronic bronchitis, chronic obstructive pulmonary disease), respiratory cancers, and hospitalisations for respiratory and cardiovascular causes related to ambient air pollution). The study arrives at an overall cost of between 0.9 billion euros and 1.8 billion euros per year which is again smaller than my estimate of the effects of a 1 $\mu g/m^3$ change in air pollution levels. In a study relying similarly on dose response estimates but using UK data, Pimpin et al. (2018) estimate that a 1 $\mu g/m^3$ reduction in population exposure to PM2.5 and NO2 would result in £1.42 billion and £353.3 million avoided, respectively, in NHS and social care costs between 2017 and 2035. This corresponds to a saving of only £98.5 million per year in a population of comparable size to that of France (the UK population is 66.65 million compared to 67.06 million in France in 2019). This is again much lower than the estimated effects in the present study. Again, only a limited number of health conditions have been considered (asthma, COPD, coronary heart disease, stroke, type 2 diabetes, dementia and lung cancer). While these studies clearly state that the health care cost estimates are conservative, the extent to which total effects have been underestimated has been unknown. My estimates allow to put into perspective by just how much total health care costs have been underestimated to date.

This study presents evidence of non-negligible health care costs caused by acute (short-term) exposure to air pollution at levels that are on average below current legal limits. The estimates presented here do not take into account the potentially large health effects of long-term exposure, but the estimated costs of short-term exposure alone suggest that there are considerable benefits to further reducing air pollution below current levels. EU air quality rules are presently being revised. One of the policy changes being discussed is a closer alignment of EU air quality standards with scientific knowledge, including the latest recommendations of the World Health Organization (WHO).[2] This planned revision is a step in the good direction. While the WHO limit values are not more stringent than the current EU framework for NO2 and O3, the revision would result in a reduction of the limit values for PM10 from an annual average of 40 $\mu g/m^3$ to 20 $\mu g/m^3$ and for PM2.5 from 25 $\mu g/m^3$ to 10 $\mu g/m^3$. However, this study estimates sizeable health care costs caused by levels of air pollution that are on average below or close to the limit values proposed by the WHO. This suggests that even stricter regulation than that of the WHO could still result in significant savings for health care systems. Another argument for a further reduction in air pollution is a

[2] `https://ec.europa.eu/environment/air/quality/revision_of_the_aaq_directives.htm`

concern for equity. The study provides evidence for significant heterogeneity of effects across patient characteristics and postcode areas, indicating that air pollution reduction policies have the potential to reduce health inequalities.

The rest of the paper is organised as follows. Section 2 provides a brief background on the health impacts of air pollution, air quality in France and the relation between wind speed, strikes in the public transport sector and air pollution levels. Section 3 describes my data, section 4 describes the empirical strategy, section 5 presents results, and Section 6 discusses the findings and concludes.

# 2. Background

## *2.1. Health effects of air pollution and air quality in France*

Air pollution is the single largest environmental risk to the health of Europeans, with particulate matter (PM), nitrogen dioxide (NO2) and ground-level ozone (O3) being the pollutants of greatest concern (EEA, 2020). Exposure to PM2.5 has been estimated to be responsible for around 400,000 premature deaths in Europe every year whereas exposure to NO2 and O3 were responsible for around 70,000 and 15,000 premature deaths in 2017, respectively (Maguire et al., 2020). Air pollution has various health effects. Short-term exposure to air pollution is closely related to Chronic Obstructive Pulmonary Disease (COPD), cough, shortness of breath, wheezing, asthma, respiratory disease, and high rates of hospitalisation. NO2 is an irritant of the respiratory system as it penetrates deep in the lung, inducing respiratory diseases, coughing, wheezing, and even pulmonary edema when inhaled at high levels. Systems other than respiratory ones can be involved, as symptoms such as eye, throat, and nose irritation have been registered. Small particulate matter of less than 10 or 2.5 microns in diameter (PM10 and PM2.5) bypass the body's defences against dust, penetrating deep into the respiratory system. They also comprise a mixture of health-harming substances, such as heavy metals, sulphurs, carbon compounds, and carcinogens including benzene derivatives. Ground-level ozone (O3) is key factor in chronic respiratory diseases such as asthma. Young children, the elderly, and people with lung disease are especially vulnerable to air pollution. The health of susceptible and sensitive individuals can be impacted even on low air pollution days (for a review, see for example Manisalidis et al. (2020)).

Legal air quality standards in France concern levels of nitrogen dioxide (NO2), oxides

of nitrogen (NOx), sulphur dioxide (SO2), lead (Pb), particulate matter 10 micrometers or less in diameter (PM10) and 2.5 micrometers or less in diameter (PM2.5), carbon monoxide (CO), benzene (C6H6), ozone (O3), as well as concentrations of arsenic, cadmium, nickel, and benzo[a]pyrene. See Table A1 for a summary of current French air quality standards for the pollutants considered in this study. Air quality in France improved globally over the period 2000-2018 following the implementation for several years of strategies and action plans in various sectors of activity (Farret et al., 2019). Exceedances of regulatory air quality standards still persist, but they are fewer than in the past and affect fewer areas (mainly near road traffic). Figure 3 shows daily mean and daily maximum hourly pollution levels relative to the French limit values. Pollution levels are mostly well below the limit value, which means that this study focuses on the impact of pollution levels that are generally considered safe.

### *2.2. Public transport strikes, wind speed and their effects on air pollution levels*

Strikes in the public transport sector are not uncommon in France. For example, there were an average of 21 separate national strikes per year at SNCF, the French national railway company between 2015 and 2019.[3] Since 2007, public transport service employees are obliged to indicate forty-eight hours in advance that they intend to go on strike to enable local authorities to reorganise the most important services, substituting non-strikers for strikers. However, this law did not establish a real minimum service obligation in public transport as it does not allow the requisitioning of striking employees. When a large share of the workforce goes on strike, the transport operator cannot redeploy non-strikers throughout the network for lack of human resources.[4] Public transport in France is generally well developed and account for 19.4% of all passenger-kilometers travelled in France in 2018. Aside the well equipped Paris area, other regions count 11 metro lines, 65 tramways (in 2017) and over 3691 bus lines (in 2012) (Commissariat général au développement durable, 2015, 2020). Public transport strikes are therefore likely to affect an important part of the French population, especially individuals living in urban areas.

[3]Calculated using data from `https://ressources.data.sncf.com`.

[4]Law n°2007-1224 of 21 August 2007 ”on social dialogue and the continuity of public service in regular land passenger transport” (JO, 22 August 2007, p. 13 956) voted on 2 August 2007 under the Fillon II government. See `https://www.legifrance.gouv.fr/affichTexte.do?cidTexte=JORFTEXT000000428994&categorieLien=id`.

It has been shown that road traffic volume and travel times increase on days of public transport strikes as many travellers switch to cars. Several studies also established correlations between periods of strike and increases in air pollution (van Exel and Rietveld, 2001; Bauernschuster et al., 2017; Basagaña et al., 2018; Godzinski and Suarez Castillo, 2019). Increased air pollution following increased road traffic is to be expected. In Europe, road traffic is estimated to be responsible for around 28% of the total emissions of nitrogen oxides (NOx) which are precursor emissions to both particulate matter and ground-level ozone. Concerning particulate matter and ozone, the total contribution of road transport is more difficult to quantify. While particulate matter is also directly emitted from cars, it is mostly created by secondary formation from precursor emissions such as NOx. Although road transport only accounts for 2.88% and 5.39% of primary PM 10 and PM 2.5 emissions, it is estimated that traffic contributes for up to 30% of total particulate emissions (primary and secondary PM) in European cities. Ground-level ozone is a secondary pollutant which is not directly emitted by traffic but formed by the influence of solar radiation from the precursors NOx and volatile organic compounds (VOC). Traffic is the main source (> 50%) of these ozone precursors. The processes of ozone formation and accumulation are complex. Nitrogen dioxide and oxygen react, which results in nitrogen monoxide and ozone.[5] Being an equilibrium reaction, the reaction also works in the other direction whereby ozone gets degraded again. This degradation occurs more often in cities as there are higher levels of NO due to traffic which react with ozone to form NO2. It also explains why short-term decreases in traffic (decrease in the NO concentration) can have adverse effect on ozone pollution (IRCEL, 2020).

In my data, NO2 and ozone are generally inversely related which is consistent with the pollution dynamics described above. On days of strike, I find increases in daily NO2 levels whereas ozone levels decrease. The relation between public transport strikes and particulate matter pollution is inconclusive. I see an increase in particle pollution on the first day of the strike, but a decrease on the second day. The lack of a clear increase in PM on strike days is not surprising considering that PM is mostly created by secondary formation from precursor emissions, which means that the link between PM and road traffic emissions is mostly indirect. See Table 2 and Table A6 in the appendix for the coefficients from regressions of the pollutants on the strike instruments (first stage regression). Figure 1 graphically illustrates the relationship between public transport strikes and NO2 pollution by showing maps of NO2 pollution at postcode level one day before, one day during and two days after a national public transport strike. Levels of NO2 visibly increase on the day of

[5]Simplified reaction equation: NO2 + O2 (+ solar UV-light, + heat) $\rightarrow$ NO + O3

the national public transport strike relative to the days before and after.

It is generally well established that wind speed strongly affects the degree of accumulation of air pollutants near emission sources such as traffic in urban environments. Wind carries air contaminants away from their source, causing them to disperse. In general, the higher the wind speed, the more contaminants are dispersed and the lower their concentration (Jones et al., 2010; Pearce et al., 2011; Grundström et al., 2015; Cichowicz et al., 2020). This is confirmed in my data. I find that pollution is higher on days of lower wind speed. See Tables 2 and A6 in the appendix for the coefficients from regressions of the pollutants on the wind instruments (first stage regression) where low wind is defined as below average wind speed. Figure 2 graphically illustrates the relationship between wind speed and NO2 pollution by showing maps of NO2 pollution and wind speed at postcode level for two days of generally low wind speed and two days of generally high wind speed. NO2 concentration is visibly higher when wind speed is low.

# 3. Data

I combine administrative data on health care reimbursements with reanalysis data on pollution levels and weather conditions, as well as data on public transport strikes for France from 2015 to 2018 which I merge by day and by postcode area.[6]

## *3.1. Health care use and costs*

I use administrative data on health care reimbursements from the French National System of Health Data (SNDS for *Système National des Données de Santé*) covering the period 2015 to 2018. The French health care system is based on universal coverage by one of several health care insurance plans. The SNDS database merges anonymous information of reimbursed claims from all these plans and is also linked to the national hospital-discharge summaries database system. The data covers 98.8% of the French population, over 66 million persons, from birth or immigration to death or emigration, making it possibly the world's largest continuous homogeneous claims database. The database provides information on the nature of medical acts and associated costs of treatment for all types of health care, including physician visits, drug purchases, and hospital care. The information is available

[6] France is divided into around 6,000 postcodes.

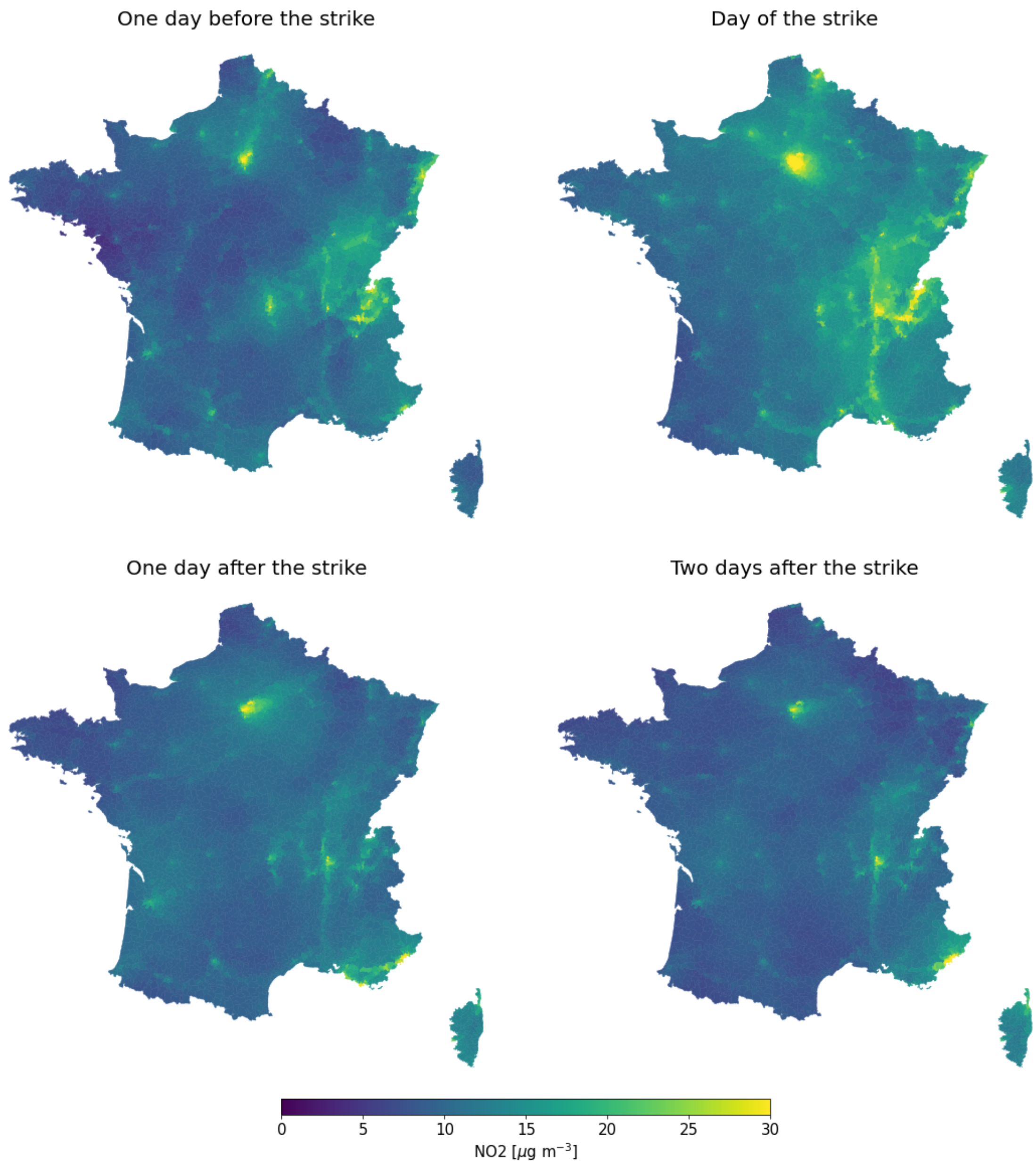


Figure 1.Level of NO2 pollution for four consecutive days, one day before a national strike, the day of the strike and one and two days after the strike.

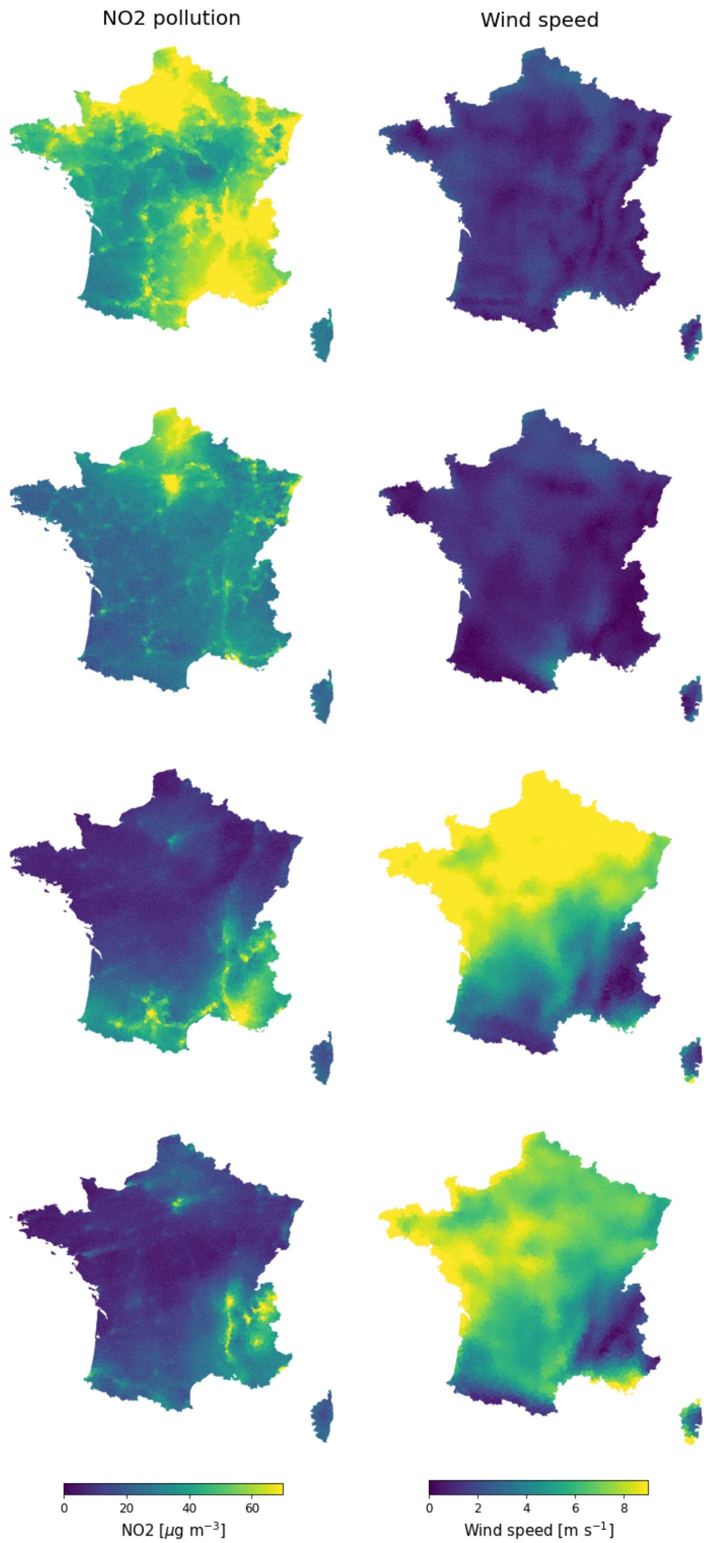


Figure 2.Level of NO2 and wind speed for two days of low wind speed (rows 1 and 2) and two days of high wind speed (rows 3 and 4).

by exact date of care and also includes codes for the classification of medical acts into medical specialties. Some data on patient characteristics are also available, including patient age, gender, information on chronic health conditions, and place of residence at postcode area level.

I conduct the study on a representative sample of this database, called the general sample of beneficiaries (EGB for *Echantillon Généraliste de Bénéficiaires*). This is the 1/97th random permanent representative sample of SNDS. The EGB facilitates the conduct of longitudinal studies as beneficiaries are identified through their national identification number, a unique personal identification, which allows to follow them over time. The EGB permits tracing back patients' health care use history. See Tuppin et al. (2010) and Bezin et al. (2017) for more information on the EGB. For most analyses, I aggregate the individual-level data on health care use and cost by the patient's postcode area of residence. For heterogeneity analyses, I additionally group by patient characteristics.

A limitation of the SNDS is that it does not contain any direct measure of the patient's socioeconomic status (SES). However, it provides information concerning the patient's complementary insurance plan including information on whether the individual subscribed to any plan, the choice of the insurance provider and whether the individual is covered by the CMUc (*Couverture médicale universelle complémentaire*), a state funded complementary insurance plan available to low-income individuals. I use this information to approximate SES, supposing that coverage by CMUc indicates low SES.

## *3.2. Air pollution*

I exploit reanalysis data on hourly concentrations of NO2, O3, PM10, and PM2.5 provided by the French National Institute for Industrial Environment and Risks (INERIS for *"Institut national de l'environnement industriel et des risques"*). The data comes in the form of raster files with high spatial resolution (cell size of about 4x4 km). I convert the hourly data into daily means and maximum values and superpose the raster data with a shapefile of France containing administrative boundaries at the postcode area to extract daily pollution levels by postcode area.

Reanalysis data offers substantial improvements over data from measurement stations. The number of monitoring stations is limited (for example, Figure A1 in the appendix shows a map of the spatial distribution of NO2 measuring stations in France) and can

vary over space and time in a non-random order. Using data from monitoring stations implies assuming that the pollution concentration is homogeneous within a given radius around the station, potentially generating a mismatch between the true and assigned level of pollution especially for locations situated farther away from the measurement stations. In many studies, researchers interpolate data points using weights of different nature to obtain information for locations far from the monitoring stations (see for example Currie and Neidell (2005); Knittel et al. (2016); Schlenker and Walker (2015)). However, interpolating pollution levels by using simple distance weights neglects meteorological and geographical factors which influence pollution dispersion in crucial ways. The reanalysis data from INERIS combines information from measurement stations with a climate model rather than using a statistical procedure to interpolate between observations to address this issue.

### *3.3. Meteorological conditions*

I use data on hourly wind speed, wind direction, temperature and precipitation from the ERA5 global land-surface data set which is produced by the Copernicus Climate Change Service (C3S) at the European Centre for Medium-Range Weather Forecasts (ECMWF). This is the fifth generation of the ECMWF atmospheric reanalysis of the global climate. The data is freely available online at `https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview`. These data are in the form of raster files with a spatial resolution of 9x9 km2. I convert the data into daily averages and overlay the raster data with a shapefile of France containing the administrative boundaries at postcode level to obtain the data per postcode area.

Reanalysis combines model data with past observations from measurement stations into a globally complete and consistent dataset using the laws of physics. This offers improvements over using data from measurement stations because using such data usually implies assuming that the level of the measured variable is homogeneous within a given radius around the station. This potentially generates a mismatch between the true and assigned level of the variable especially for locations situated farther away from the measurement stations.

### *3.4. Public transport strikes and other additional data*

Information on the dates and locations of public transport strikes are collected manually through Google searches and from the website `https://www.cestlagreve.fr/`. I consider any strike affecting train, tram, metro or bus services. Based on the collected data, I construct an indicator variable equal to one when a particular post code area was affected by public transport strikes at any given day. I also construct the distance in km between the postcode area centroid to the nearest location of strike to look at potential spillover effects of strikes in nearby locations. I construct similar indicator variables for strikes at the department and national level. Finally, I exploit data on the percentage of agents at the French National Railway Company (SNCF for *"Société nationale des chemins de fer français"*) who followed the call to strike during national strike movements as measure of strike intensity. This data is available at `https://ressources.data.sncf.com/`.

I use additional data on postcode-level average household income, Gini Index (measure of income inequality ranging from 0 to 1, 1 being most unequal), and unemployment rate from the Localized Social and Fiscal File (FiLoSoFi for *Fichier Localisé Social et Fiscal* in French) provided by the French National Institute of Statistics and Economic Studies (INSEE for Institut national de la statistique et des études économiques in French). This database generally includes income distribution indicators reported by households, for all households and by household category and is publicly availably online from the website `https://www.insee.fr/fr/metadonnees/source/serie/s1172`. Additional data on holidays in France are obtained from `https://www.data.gouv.fr/en/datasets/jours-feries-en-france`.

### *Summary statistics*

Table A2 in the appendix presents summary statistics for the entire sample consisting of 8,835,995 postcode-day observations. I run several regressions on a sub-sample comprising the 10% most densely populated postcode areas and another sub-sample comprising only the postcode areas that make up the 70 largest French cities (about 2% of the sample). The summary statistics for these samples are presented in Tables A3 and A4 in the appendix. In the whole sample, the daily average healthcare expenditure is 513.76 Euros with a standard deviation of 1415.4. Mean daily concentration of NO2 is 13.8 (standard deviation 8.44); concentration of PM 10 is 16.61 (sd 8.47); concentrations of of PM 2.5 is 10.58 (sd 7.44) and concentrations of O3 is 55.64 (sd 20.32) micrograms per cubic meter. Average NO2 and

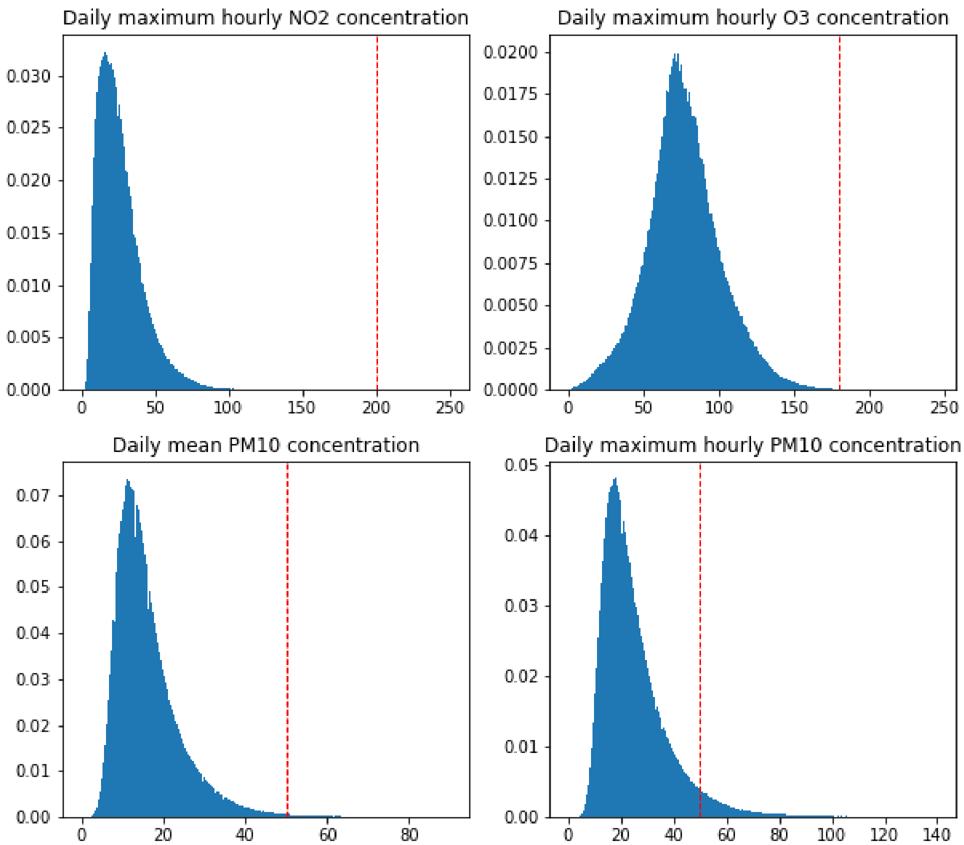


Figure 3.Level of pollutants relative to the limit values presented in Table A1.

PM pollution levels are higher and O3 levels are lower in the reduced samples which should be unsurprising as these include mostly observations in urban areas[7]. Average spending is higher in the reduced samples. Postcode, department and/or national level public transport sector strikes are happening in around 30% of the postcode-day observations.

Pollution concentrations in France are generally situated below the limit value that is considered safe for human health. This can be seen from Figure 3 which displays the distribution of daily maximum hourly and daily mean pollutant concentration together with the corresponding limit value. Figure 4 shows how average health care expenditure and pollutants vary by day of the week and month, showing significant cyclical changes over the week and seasons.

[7]Note that NO2 and PM are negatively correlated with O3 as discussed in section 2.

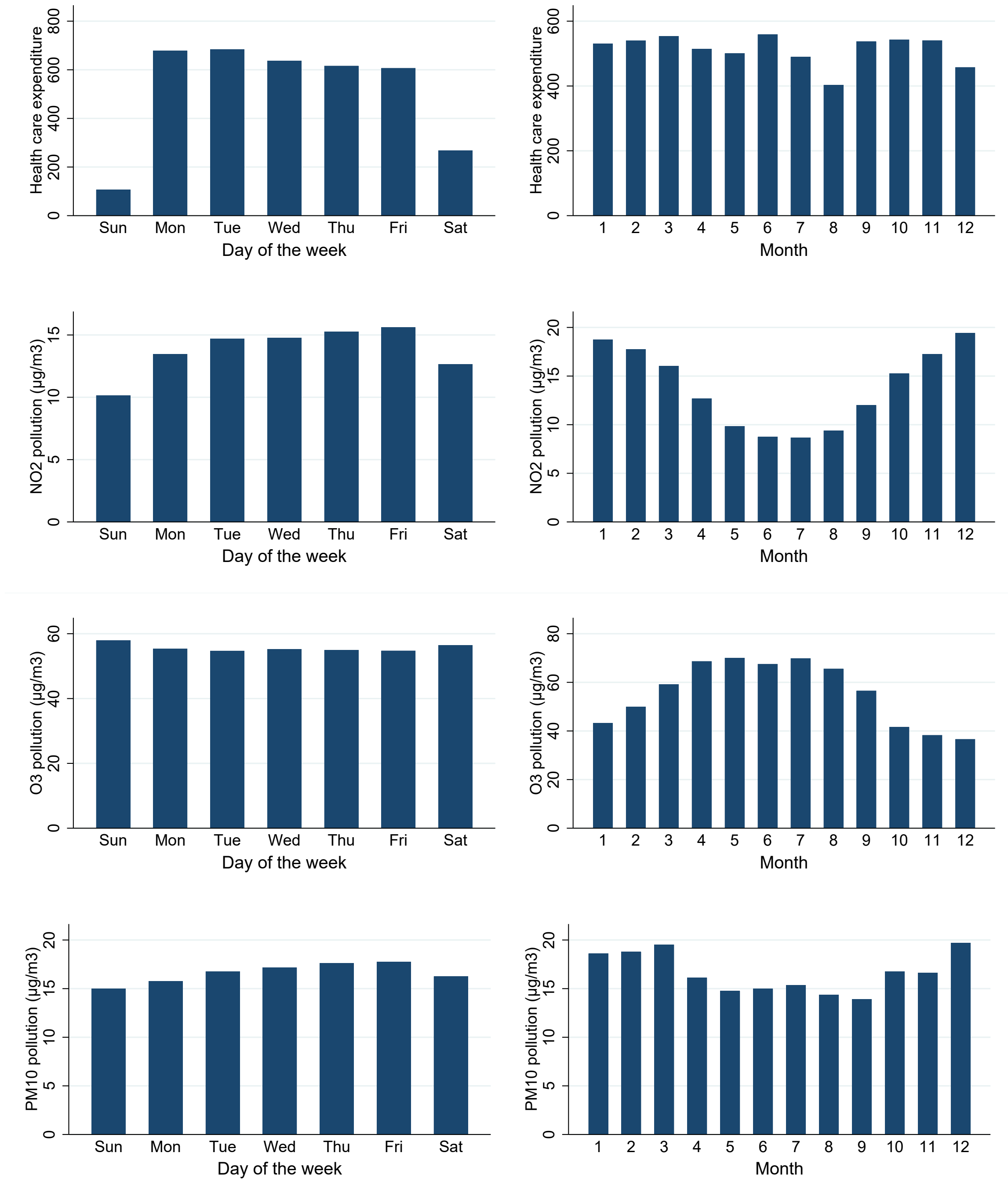


Figure 4.Mean of health care expenditure and pollutants by day of the week and month.

# 4. Method

## *4.1. Location and time fixed effects model*

The objective is to estimate the causal short-run effect of exposure to air pollution on health care use and costs. Exploiting daily variation in the intensity of air pollution at the postcode area level, I estimate the following model:

$$H_{dpc} = \beta P_{dpx} + \alpha_p + \alpha_{dow} + \alpha_{mdep} + \alpha_{y/my} + \gamma X_{pd} + \epsilon_{xdp}, \tag{4.1}$$

where $H_{dpc}$ denotes health care use or cost on day $d$ in postcode area $p$ and for medical specialty $c$. I regress this on the pollution level $P_{dpx}$ of pollutant $x$ on day $d$ in postcode area $p$. Individuals can spatially sort according to preferences and characteristics that can be correlated with both their health status and their level of exposure to pollution. I control for location fixed effects at the level of the postcode area $\alpha_p$ to account for the possibility that unobserved site characteristics are correlated with both average pollution levels and average health care use. I also flexibly control for seasonality in air pollution and health care use by including a range of time fixed effects. I include day-of-week ($\alpha_{dow}$), month-by-department ($\alpha_{mdep}$), and month-by-year ($\alpha_{my}$) fixed effects. Department-by-month fixed effects flexibly control for any seasonal correlation between pollution and health that are allowed to vary by department.[8] The month-by-year fixed effects control for common time-varying shocks, such as changes in environmental policy. I denote $X_{pd}$ the vector of additional time-varying covariates which include variable indicating holidays and indicator variables for daily mean temperatures and daily precipitation falling into 10 bins by decile and different possible interactions of these weather indicator variables. In robustness checks, I try out alternative model specifications with different more or less flexible time fixed effect structures and weather controls. Standard errors are clustered at the postcode level. In some specifications, I include up to three lags of the air pollutants and weather variables to consider the possibility that pollution build-up over the past days may impact health outcomes.

[8]France is divided administratively into ninety-five departments which are smaller than the regions, of which there are 18, but much larger than the communes which are analogous to the civil townships and incorporated municipalities in the United States and Canada. There are over $34,000$ communes in France that are are served by around 6,000 postcodes.

## *4.2. Wind speed and public transport sector strikes as instruments for air pollution*

Both air pollution levels and health care use change cyclically throughout the week (see Figure 4) and appear to be correlated with economic activity. A possible cause for concern is that the fixed effect structure in equation (4.1) does not correctly purge these effects. To address this potential issue, I estimate instrumental variable (IV) models in which I use wind speed as instrument for air pollution levels. Wind speed is plausibly exogenous to economic activity, which means that the IV approach should allow me to estimate the effects of air pollution on health care use and costs without accidentally capturing correlations due to economic activity.

It is possible that individuals chose their place of residence not only considering average pollution levels but their decision may also be influenced by the range of variation in pollution levels. For example, individuals may want to avoid proximity to pollution sources that produce extreme levels of pollution even if such levels occur less frequently and do not translate into a higher average level of pollution. If the range of variation in pollution is a function of unobserved individual characteristics and if the health effects of high deviations from average pollution level differ compared to relatively smaller deviations, then my estimates could still be biased despite controlling for all location and spatial fixed effects and despite the instrumental variable approach proposed above. A potential solution to this problem is to consider events that shift pollutant concentrations to levels that are not commonly observed and that are unanticipated. I consider episodes of strike in the public transport sector to be such an event and use it as instrument for air pollution levels.

A valid instrumental variables approach requires that the instruments (i) be sufficiently correlated with the endogenous variable of interest and (ii) not be correlated with any unobserved determinants of the outcome of interest (exclusion restriction). In the present case this means that wind speed must be sufficiently correlated with air pollution and it must affect health care use only through its influence on pollution levels. I find that pollution levels are indeed correlated with wind speed. Pollution levels in big cities are higher on days with low wind speed, likely because pollution that originated inside the city is carried away on days of high wind speed. It is plausible that the exclusion restriction holds. Common levels of wind speed are unlikely to have a direct effect on health care use. Extremely high wind speed could potentially increase health care use due to a higher risk of accidents but not due to pollution exposure because pollution levels are lower on days of high wind speeds. I do

not find evidence in the data for increased health care use on days of high or exceptionally high wind speed. Similarly, public transport strikes must be sufficiently correlated with air pollution and it must affect health care use only through its influence on pollution levels. I show that pollution levels in the big cities are exceptionally high on days of public transport sector strike. The exclusion restriction for the strike instrument is likely to hold at least for some selected medical specialties such as cardio-vascular and respiratory care which I analyse separately from other medical specialties that could be affected by the occurrence of strikes (such as trauma surgery), or specialties that are likely to be unresponsive to both the occurrence of strikes or pollution (for example plastic surgery) and serve mainly as placebo.

I use public transport sector strikes and not strikes more generally which means that most people should continue to go to work with the only major change being the use of a different means of transportation to get to their workplace. However, it is possible that some individuals are taking the day off in case it is too difficult to get to their workplace. If these individuals decide to use the newly gained time to go seek for (non-urgent) health care that they would otherwise have looked for at a later moment, then my estimates could pick up this effect rather than the effect of strike-induced pollution. It is unlikely that this happens on a large enough scale for my estimates to be noticeably biased.

Formally, the first stage specification is as follows:

$$P_{xdp} = \beta_0 IV_{dp} + \alpha_p + \alpha_{dow} + \alpha_{mdep} + \alpha_{y/my} + \delta X_{pd} + \epsilon_{xdp} \tag{4.2}$$

where $P_{xdp}$ denotes the measure of pollution of pollutant $x$ on day $d$ in postcode area $p$, $IV_{dp}$ is an indicator variable equal to one if wind speed is below average on day $d$ in post code area $p$ and zero otherwise. Alternatively, $IV_{dp}$ is an indicator variable equal to one if a public transport strike occurs on day $d$ in post code area $p$ and zero otherwise. The control variables and the fixed effects are the same as in equation 4.1.

The data are very detailed which allows me to thoroughly explore treatment effect heterogeneity. I study heterogeneous effects across a range of patient characteristics such as age, sex, chronic disease status as well as postcode area characteristics including postcode-level average income, Gini Index and unemployment rate. I hypothesise that children and the elderly, people with chronic diseases and those living in poorer, more unequal and higher unemployment areas are more strongly affected by air pollution exposure.

# 5. Results

## 5.1. *Main results*

Table 1 reports the main estimates of the relationship between daily NO2 and O3 pollution and total health care costs. Column 1 shows that each 1 µg/m3 increase in daily NO2 (about 7.2% of the mean) is associated with 5.59 Euro of additional health care expenditure the same day which corresponds to a 1.1% increase relative to the average daily health care spending. Each 1 µg/m3 increase in daily O3 (about 1.8% of the mean) increases spending by 0.79 Euro or 0.2% relative to the average daily spending. Columns 2 and 3 present the corresponding IV estimates. The estimates from the model using wind as IV imply that each 1 µg/m3 increase in daily NO2 cause an increase of 7.57 Euro in aggregate health care spending whereas each each 1 µg/m3 in daily O3 causes an increase of 3.94 Euro which translates into an increase of 1.5% and 0.8% relative to the average daily spending. Using strike as instrument yields even larger estimates. Daily spending increases by 21.68 Euros for each 1 µg/m3 in NO2 and by 19.68 Euro for each 1 µg/m3 in O3. This corresponds to a 4.2% and 3.8% increase in daily spending. The IV estimates are larger than the OLS estimates, suggesting that OLS estimation is biased. Interestingly, OLS regression leads me to underestimate rather than overestimate the effects.

Table 1: OLS and IV estimates of effect of NO2 and O3 on health care expenditure

| | Total spending - entire France | | | Total spending - 70 biggest cities | | |
|---|---|---|---|---|---|---|
| | OLS<br>(1) | Wind IV<br>(2) | Strike IV<br>(3) | OLS<br>(4) | Wind IV<br>(5) | Strike IV<br>(6) |
| NO2 mean | 5.59*** | 7.57*** | 21.68*** | 15.08*** | 24.83** | 165.1** |
| | (0.382) | (1.240) | (2.061) | (2.405) | (9.480) | (58.090) |
| Effect relative to mean (%) | 1.1 | 1.5 | 4.2 | 0.4 | 0.7 | 4.6 |
| O3 mean | 0.79*** | 3.94*** | 19.68*** | 5.07*** | 22.10** | 157.2*** |
| | (0.057) | (0.591) | (1.947) | (0.711) | (7.566) | (43.999) |
| Effect relative to mean (%) | 0.2 | 0.8 | 3.8 | 0.1 | 0.6 | 4.4 |
| Constant | -56.37** | | | -298.0 | | |
| | (19.339) | | | (383.099) | | |
| Dependent variable mean | 513.76 | 513.76 | 513.76 | 3550.96 | 3550.96 | 3550.96 |
| Observations | 8495951 | 8484329 | 6539870 | 215497 | 215203 | 162491 |
| First-stage F-stat | | 8805.0 | 3765.3 | | 551.1 | 162.3 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

The effects are larger when I restrict the sample to include only the most populated areas. Columns 4 to 6 report the estimates from regressions using a sample of the France's 70 biggest cities which corresponds to 2% of the whole sample. The estimates are 2.7 to 7.6 times bigger than the estimates from the regression on the whole sample. Different samples selected according to total population or population density yield qualitatively similar results. For example, Table A5 in the appendix shows the results for a sample of the 10% most populated postcode areas where the estimates are larger than the estimates for the whole sample but smaller than the results for the sample of 70 biggest cities[9]. This suggests that the effects of pollution are concentrated in urban areas, potentially due to non-linear effects of pollution. A 1 µg/m3 increase in pollution in an area with higher average pollution levels could have larger effects on health relative to the same increase in pollution in an areas with lower average pollution levels. I further investigate the existence of such non-linear effects in the heterogeneity analyses presented in the next subsection.

The first stage F-statistics, reported at the bottom of Table 1, are generally large, suggesting that there is no problem of weak instruments. Tables 2 shows the first stage regressions for the whole sample. See Table A6 in the appendix for the first stage using small sample of the 70 biggest cities. I include both O3 and NO2 in the OLS regressions or simultaneously instrument for both pollutants in the IV regressions because there is an inverse relationship between these pollutants and because both pollutants are expected to have independent effects on health (see section 3). The results are qualitatively similar when I only include NO2 in the OLS model and in the strike IV model whereas the results in the wind IV model are not statistically significant anymore. See the section on robustness checks.

## *5.2. Results by location characteristics*

In this section, I present results from heterogeneity analyses based on postcode area characteristics. I separate postcode areas into quantiles according to the value of their average Gini Index (measure of inequality ranging from 0 being most equal to 1 being most unequal), unemployment rate and household income. Looking at simple averages of health care spending and pollution levels by postcode characteristics reveals substantial inequalities.

[9] I run several regressions on a sub-sample comprising the 10% most densely populated postcode areas and another sub-sample comprising only the postcode areas that make up the 70 largest French cities (about 2% of the sample). The summary statistics for these samples are presented in Tables A3 and A4 in the appendix.

Table 2: First stage regressions corresponding to the IV regressions shown in Table 1 for the entire sample

| | NO2 mean | O3 mean | PM 10 mean | NO2 mean | O3 mean | PM 10 mean |
|---|---|---|---|---|---|---|
| Low wind speed | 3.747*** | -7.264*** | 1.973*** | | | |
| | (0.026) | (0.025) | (0.018) | | | |
| Low wind speed Lag 1 | 1.526*** | -4.300*** | 1.940*** | | | |
| | (0.012) | (0.017) | (0.017) | | | |
| Low wind speed Lag 2 | 0.294*** | -1.315*** | 0.943*** | | | |
| | (0.004) | (0.012) | (0.008) | | | |
| Strike day 1 | | | | 0.0802*** | -0.200*** | -0.288*** |
| | | | | (0.007) | (0.016) | (0.008) |
| Strike day 2 | | | | 1.087*** | -1.107*** | 0.248*** |
| | | | | (0.013) | (0.026) | (0.019) |
| Strike day 3 | | | | 0.592*** | -1.952*** | -0.358*** |
| | | | | (0.015) | (0.030) | (0.018) |
| Constant | 7.334*** | 85.74*** | 12.19*** | 10.64*** | 80.02*** | 14.42*** |
| | (0.054) | (0.115) | (0.067) | (0.051) | (0.124) | (0.065) |
| Observations | 8484454 | 8484454 | 8484454 | 6539974 | 6539974 | 6539974 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Figure A2 to A4 in the appendix present average health care spending and pollution levels for postcode areas separated into deciles. Average health care expenditure varies significantly by postcode area characteristics. Spending is higher in postcode areas that are more unequal and that have a higher unemployment rate. There is no clear income gradient as health care expenditure is high both in the postcode areas from the lowest the highest income decile while spending is lower in the intermedial deciles. Average NO2 pollution levels also vary substantially. Average NO2 pollution is higher in more unequal postcode areas. The relation between average NO2 pollution and average postcode area unemployment level is u-shaped with higher pollution levels in low unemployment areas and high unemployment areas. Average NO2 pollution levels drop from the first to the second income decile and then monotonously increase. NO2 levels are as high in the first income decile as in the 7th income decile. The differences in average O3 and PM pollution are much less marked.

For the regressions, I separate postcode areas into quintiles according to their average Gini Index, unemployment rate and household income, respectively. I find evidence of substantial heterogeneity, with the most disadvantaged regions being more heavily affected. Panels A and B in Table 3 present the estimates from the wind IV and strike IV model, respectively, by Gini Index quintiles. The increase in healthcare spending for a 1 µg/m3 increase in daily NO2 or O3 is 4 to 6 times stronger in the most unequal postcode area compared to the most equal quintile. However, the effect relative to the mean is relatively similar or even feebler in the most unequal quintiles because health care spending is on average higher in more unequal postcode areas. Panels C and D present results by unemployment rate quintiles. The effects are in between 1.4 to 2.1 times stronger in the postcode area quintile with the highest unemployment rate compared to the postcode area with the lowest unemployment rate. Yet again, the effect relative to the mean is similar between the first and last quintile because of the higher average health care spending in the postcode areas with the highest unemployment rates compared to the areas with the lowest unemployment rates.

Tables A7 to A12 in the appendix show all results including coefficients from OLS regressions by Gini Index, unemployment rate and income quintiles for the whole sample and the sample including the 10% most populated postcode areas. The results by Gini Index and unemployment rate are qualitatively similar to what has been presented in Table 3. The effects by income quintiles are not conclusive (Tables A9 and A12). The results for the smaller sample of the 70 biggest cities are mostly not statistically significant and are therefore not shown.

Table 3: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area Gini Index and unemployment quintiles (whole sample)

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| ***Panel A**: Wind IV, heterogeneity by Gini Index quintile (1st quintile is most equal)* | | | | | |
| NO2 mean | 5.386** | 9.364*** | 4.940* | 9.412*** | 20.08*** |
| | (2.004) | (2.570) | (2.419) | (2.781) | (3.998) |
| Effect relative to mean (%) | 1.5 | 2.0 | 0.9 | 1.4 | 1.3 |
| O3 mean | 2.423** | 4.872*** | 3.056* | 5.643*** | 14.42*** |
| | (0.892) | (1.216) | (1.280) | (1.512) | (2.602) |
| Effect relative to mean (%) | 0.7 | 1.1 | 0.6 | 0.9 | 1.0 |
| Dependent variable mean | 349.3 | 461.02 | 526.54 | 658.89 | 1505.1 |
| Observations | 1157331 | 1086203 | 1115756 | 1073445 | 1032594 |
| First-stage F-stat | 1877.0 | 1462.5 | 1572.2 | 1397.7 | 1479.6 |
| ***Panel B**: Strike IV, heterogeneity by Gini Index quintile (1st quintile is most equal)* | | | | | |
| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
| NO2 mean | 20.65*** | 14.96*** | 21.80*** | 29.90*** | 52.13*** |
| | (4.314) | (4.205) | (4.824) | (4.737) | (8.566) |
| Effect relative to mean (%) | 5.9 | 3.2 | 4.1 | 4.5 | 3.5 |
| O3 mean | 5.256* | 15.59*** | 20.66*** | 14.67*** | 32.49*** |
| | (2.457) | (3.855) | (3.813) | (3.677) | (6.833) |
| Effect relative to mean (%) | 1.5 | 3.4 | 3.9 | 2.2 | 2.2 |
| Dependent variable mean | 349.3 | 461.02 | 526.54 | 658.89 | 1505.1 |
| Observations | 1158917 | 1087691 | 1117284 | 1074915 | 1034008 |
| First-stage F-stat | 501.2 | 403.3 | 461.3 | 457.4 | 502.2 |
| ***Panel C**: Wind IV, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)* | | | | | |
| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
| NO2 mean | 6.142*** | 12.60*** | 10.77** | 10.23* | 8.902* |
| | (1.827) | (2.628) | (3.420) | (4.771) | (3.715) |
| Effect relative to mean (%) | 1.1 | 2.2 | 1.7 | 1.3 | 1.0 |
| O3 mean | 3.512*** | 7.066*** | 5.933*** | 6.036* | 5.761** |
| | (0.951) | (1.342) | (1.632) | (2.508) | (2.215) |
| Effect relative to mean (%) | 0.6 | 1.2 | 0.9 | 0.7 | 0.6 |
| Dependent variable mean | 549.83 | 583.04 | 634.71 | 804.82 | 915.47 |
| Observations | 1314531 | 1000127 | 977515 | 1120134 | 1053022 |
| First-stage F-stat | 1528.6 | 1140.1 | 1150.9 | 1348.6 | 1604.3 |
| ***Panel D**: Strike IV, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)* | | | | | |
| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
| NO2 mean | 20.93*** | 26.74*** | 24.17*** | 34.52*** | 44.88*** |
| | (4.933) | (5.357) | (6.133) | (7.786) | (6.747) |
| Effect relative to mean (%) | 3.8 | 4.6 | 3.8 | 4.3 | 4.9 |
| O3 mean | 15.69*** | 15.49*** | 9.346* | 19.35*** | 26.24*** |
| | (3.272) | (3.918) | (4.362) | (5.336) | (5.448) |
| Effect relative to mean (%) | 2.9 | 2.7 | 1.5 | 2.4 | 2.9 |
| Dependent variable mean | 549.83 | 583.04 | 634.71 | 804.82 | 915.47 |
| Observations | 1316331 | 1001497 | 978855 | 1121668 | 1054464 |
| First-stage F-stat | 537.1 | 393.4 | 340.5 | 450.9 | 584.0 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, month-by-department, month-by-year and postcode fixed effects.

Separating the sample into quintiles according to average pollution levels leads to ambiguous results (see Tables A13 and A14 in the appendix).

### *5.3. Results by patient characteristics*

Many of the existing studies on the health effect of air pollution focus on the young or elderly populations as these populations are generally considered to be the most vulnerable. I find evidence of effects across all age categories, suggesting that adverse health effects also manifest in parts of the population that are less often considered. Tables A15 to A16 in the appendix show OLS and IV model results for regressions run separately for 10-year age groups. The estimated level effect is higher for older individuals of 40 years and above, but the effect relative to the age group's average expenditure is more similar across age groups. Finding effects in all age groups could be explained by the fact that I am looking at overall health care costs, which include the costs of treating milder health consequences that are likely to occur in all age groups, whereas a study of the impact on mortality might have revealed that the effects are concentrated in the young and the old, with mortality being a rather extreme outcome likely to affect only the most vulnerable.

I further explore whether individuals with preexisting health conditions are more vulnerable to pollution exposure by dividing the sample into those who have a chronic disease and those who do not. This investigation remains inconclusive. The results from the OLS and wind IV regressions suggest that the effect of pollution health care spending are stronger for individuals with a chronic disease. The results from the strike IV, however, point in the opposite direction. See Table A18 in the appendix. Finally, I investigate whether effects differ for individuals who are covered by the CMUc (*Couverture médicale universelle complémentaire*), a state funded complementary insurance plan available to low-income individuals. I use this information to approximate socioeconomic status (SES), supposing that coverage by CMUc indicates low SES. I do not find that individuals who are covered by the CMUc are affected more than individuals covered by regular insurance plans. Table A19 in the appendix shows that the effect relative to the average spending of the two groups is similar.

## *5.4. Results by medical specialty*

I examine what types of health conditions are affected by exposure to air pollution by running separate regressions for 15 different categories of medical specialties. While interesting in its own right, this exercise also serves as a sanity check. I consider both medical specialties that should be affected by air pollution and medical specialties that should not be affected as placebos. Among the categories that I expect to be affected are family practice (primary care physician), otorhinolaryngology, ophthalmology, stomatology, dentistry, cardiology and vascular medicine, pneumology, neurology, genecology, abmulance services. The placebo specialties include gastro-hepatology, rhumatology, nephrology and plastic surgery.

Table A20 shows the OLS results by medical specialty for the entire sample. All estimates, including the estimates for the placebo categories, are positive and statistically significant. Finding that all medical categories including specialties such as rhumatology, nephrology and plastic surgery are affected suggests that there might be an issue with spurious correlation. This could happen, for example, if the day of the week effects do not allow to correctly account for the co-movements of pollution and health care activity across the week. The estimates on the placebo medical specialties become smaller and statistically not significant when I restrict the sample to the 10% most populated cities and the sample including only the 70 biggest cities (with the notable exception of plastic surgery, see Tables A21 to A22). The cyclical movements of pollution and medical activity could differ across locations in a way that a day of the week fixed effect that is common to all observations cannot account for. This hypothesis is supported by the results from regressions where I interact a dummy indicating that the day is a weekday with the location fixed effect to allow weekly cyclical movements to vary by postcode area (Tables A23 and A24[10]). I find that most of the coefficients on the placebo medical categories are less statistically significant or not significant anymore.

Results by medical specialty for the model using strike as instrument for air pollution are reported in Tables A25 to A29 in the appendix. The strike IV seems to at least partially address the problem of the spurious correlations. Even for the regressions on the whole sample and without interaction the weekday fixed effect with the location fixed effects, the coefficients on the placebo categories rhumatology, nephrology, and gastro-hepatology are not statistically significant. The coefficient on plastic surgery is statistically significant at

[10]Results for the entire sample are not available yet due to lack of computation power.

the 5% level. The effect on plastic surgery disappears for all other samples and the models included interacted weekday and location fixed effects. Trauma surgery should be unrelated to pollution exposure, yet the IV estimate is positive and statistically significant, probably pointing toward the limitation of using public transport strikes as instrument for air pollution exposure. Public transport strikes may have an impact on the number of accidents due to increased car traffic and, therefore, increase trauma surgery expenses, independently of their effect on pollution. Surprisingly, the coefficients on the medical specialties pneumology are not significant. I find that the results are most robust for the categories otorhinolaryngology, ophthalmology, dentistry, neurology, genecology, and abmulance services. Similar to the effects for health expenditure at the aggregate level, the IV estimates are generally larger than the OLS estimates. Estimates for the wind IV are reported in Tables A30 to A34 in the appendix. Mostly only the estimates for family medicine and ambulance services are statistically significant. For some specifications The wind IV approach is likely the more conservative approach to be taken.

### *5.5. Robustness checks*

The results are robust to alternative model specifications with different time fixed effect structures and weather controls. Table A35 in the appendix shows the main estimates of the relationship between daily NO2 and O3 pollution and total health care costs when I use month and year fixed effects rather than month-by-department and month-by-year fixed effects. The results are almost identical to the estimates from my preferred model specification shown in Table 1. Table A37 and Table A38 in the appendix show the main estimates for models excluding the vector of temperature and precipitation bins with full time fixed effects and simpler time fixed effects. However, accounting for cyclical movements in pollution and health care use across the week appears to be important. Excluding the day of the week fixed effects leads to estimates that are about 3 times larger compared to the estimates from models including the full range of time fixed effects, as shown in Table A36. The results are also robust to using different lag structures for the pollutants and weather controls (Table Table A39 in the appendix). Tables A40 and A41 in the appendix show that results are robust to using different definitions of the strike IV (a dummy equal to 1 for any day of strike, dummies for the first, second and third day of strike, etc.), but less robust to using different definitions constructions for the wind IV (dummy for low wind speed, dummies for the lag of wind speed or wind speed).

I observe important correlations between the pollutants. Both NO2 and particulate matter and O3 are generally inversely related while NO2 and PM are positively correlated (see again section 2). Due to the systematic co-movements, I cannot estimate separately the effects for PM and NO2. However, it may not be very meaningful to separate the effect of the two pollutants because NO2 is a precursor to PM and some of the health effects of NO2 are also potentially mediated through the health effects of PM. Still, I examine whether the effects of NO2 and O3 are robust to the inclusion of additional controls for particulate matter (PM10 and PM2.5) pollution. Table A42 in the appendix shows that the results remain qualitatively the same. When I focus the analysis on the effects of particulate matter and O3 pollution while adding NO2 pollution only as additional control, I find that PM10 and PM2.5 pollution increases health care spending but the effects are far less pronounced than the effects from NO2 pollution (Table A43 in the appendix). I include O3 together with either NO2 or PM in all regressions to avoid underestimating the effects of a pollutant because an increase of NO2 or PM that could lead to adverse health effects systematically coincides with a decrease of O3 which could yield health benefits. The results are not entirely robust when I look only at one pollutant without simultaneously instrumenting or at least controlling for the other observed pollutants. See Table A44 for the estimates considering only one pollutant at a time.

### *5.6. Extensions*

In further extensions of this work, I estimate the effect of air pollution on mortality, and on sick leave. Preliminary results suggest that higher in NO2 and O3 pollution leads to an increase in the number of sick days taken and increases the costs to the health care system due to sick leave payments. See Table A45 in the appendix. The results regarding mortality are not yet conclusive. I find a small effect of increased mortality when NO2 and O3 levels are higher using OLs regressions, but the results for the IV regressions are not statistically significant (Table A46 in the appendix).

I continue my investigation by exploring the use of wind direction and thermal inversions as other potential instruments for air pollution. The wind direction instrument should capture the variation in pollution due to the transport of non-local pollution (while the wind speed instrument instead captures local pollution emissions). I interact dummies for the daily average wind direction by 90-degree intervals with a dummy for the postcode area to allow the wind direction instrument to vary by location. This is very similar to the IV model

used by Deryugina et al. (2019). Thermal inversions are a weather phenomenons known to affect pollution levels. Thermal inversions are a deviation from the normal monotonic relationship between air temperature and altitude which occur in the lower troposphere (below an altitude of around 4 km). Under normal atmospheric conditions, warm air at the surface is drawn upwards as a result of its lower density. This atmospheric ventilation can help to reduce pollution levels at the surface. During a thermal inversion, however, the inversion layer prevents the normal atmospheric ventilation from taking place, trapping polluted air at the surface. I follow Dechezleprêtre et al. (2019) in defining an indicator variable of thermal inversion equal to 1 if the daily average temperature is higher at the second lowest level of the atmosphere than at the lowest level above the surface. Using wind direction as instrument yields estimates of a magnitude similar to the estimates from the strike IV models. Using thermal inversions as instrument only yields results that are borderline statistically significant. See Table A47 in the appendix.

# 6. Discussion and conclusion

This study presents evidence of non-negligible health care costs caused by exposure to pollution levels that are mostly below current legal limits. I estimate that each 1 µg/m3 increase in daily NO2 (7.2% of the mean) cause an increase of €7.57 in aggregate health care spending whereas each each 1 µg/m3 in daily O3 (1.8% of the mean) causes an increase of €3.94 which translates into an increase of 1.5% and 0.8% relative to the average daily spending. These are relatively conservative estimates, as many model specifications yield even larger estimates. The estimates in this study reflect the costs of acute (short-term) exposure to air pollution while the potentially even larger effects of long-term exposure are not considered. Yet the high costs from short-term exposure alone suggest that there are considerable benefits to reducing air pollution, as the following back-of-the-envelope calculation illustrates.

## *6.1. Back-of-the-envelope cost-benefit analysis*

The increase of €7.57 per day per postcode for a 1 $\mu g/m^3$ increase in daily NO2 results in €1.6 billion additional health care spending per year. Adding the effect for a 1

$\mu g/m^3$ increase in daily O3 amounts to €2.5 billion of additional spending per year.[11] To obtain these numbers, I assume that the daily effects of a 1 $\mu g/m^3$ increase in daily pollutant concentrations can be scaled linearly to yearly effects of a 1 $\mu g/m^3$ increase in annual average pollutant concentrations. This is a conservative approach as in the epidemiological literature the long-term health effects of air pollution exposure are generally considered more important than the short-term effects.

Compliance with the National Emission Commitment (NEC) Directive (2016/2284/EU)[12] requires France to reduce nitrogen oxides (NOx, composed of both NO2 and NO) by 50% compared to 2005 values, to be achieved from 2030. In 2005, annual NO2 concentrations in France were 17.5 $\mu g/m^3$[13], which means that France should reduce NO2 by 8.75 $\mu g/m^3$ until 2030. Given the 2017 average of 12.01 $\mu g/m^3$[14], this implies a further decrease of 3.26 $\mu g/m^3$ of annual NO2 concentration which, which I estimate will result in an annual saving of €5.2 billion in healthcare costs when France meets its commitment. This contrasts with the €9.9 billion annual costs of compliance with the NEC Directive as estimated in Amann et al. (2017). The benefits from a reduction in short-term health care costs due to the decreased NO2 pollution alone sets off 40% of the total costs of compliance with the NEC directive.

## 6.2. *Comparison of the effect size with results from previous studies*

Most studies that seek to evaluate the health costs of air pollution for cost-benefit analysis estimate the costs indirectly through simulations based on air quality and population data, baseline rates of mortality and morbidity, concentration-response parameters from the epidemiological literature, and unit economic values. Often, only a selection of health effects for which epidemiological evidence is most robust are included in these models. For example, the Environmental Benefits Mapping and Analysis Program–Community Edition (BenMAP-CE) is a tool historically used by the Environmental Protection Agency (EPA) but also widely employed by other agencies and researchers to estimate the economic impact of a

[11] The €7.57 increase per day per postcode for a total of 6,048 postcodes and in a sample the size of 1/97 of the total French population translates into $e7.57 \cdot 97 \cdot 365 \cdot 6,048 = e1,620,959,861$ health care spending per year. Similarly, the €3.94 increase in spending related to a 1 $\mu g/m^3$ increase in daily O3 translates into $e3.94 \cdot 97 \cdot 365 \cdot 6,048 = e843,669,994$ health care spending per year.

[12] Directive (EU) 2016/2284 of the European Parliament and of the Council of 14 December 2016 on the reduction of national emissions of certain atmospheric pollutants, amending Directive 2003/35/EC and repealing Directive 2001/81, `https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016L2284&from=EN`

[13] 20 ans d'évolution de la qualité de l'air cartographiés par l'Ineris, `https://www.ineris.fr/fr/recherche-appui/risques-chroniques/mesure-prevision-qualite-air/20-ans-evolution-qualite-air`

[14] Ibid.

range of clinical outcomes due to air pollution. The model's default features consider only the costs of hospital and emergency department admissions. A more complete accounting of the chain of costs would include ambulatory and other care (including physician and clinic visits, prescription drugs, supplies, and home health care) that may also increase as a result of increased air pollution. When an additional quantification of such ambulatory care is added, only a subset of health effects have been considered (for example Birnbaum et al. (2020) who consider only two disease categories, respiratory and all cardiovascular disease).

I am not aware of any other study that comprehensively quantifies health care costs in France. The evaluation of health care costs caused by air pollution has so far been only very partial, resulting in a severe underestimation of costs. To inform policy decisions, a 2015 Senate Committee of Inquiry into the economic and financial cost of air pollution[15] searched for estimates of the total costs of air pollution to the French health care system. The result was a report on two studies that considered only a fraction of the total health care costs and a recommendation that more research be conducted in this area. The first of these studies is a 2007 impact study on the costs to health insurance that was conducted by the French Agency for Environmental and Occupational Health Safety (Fontaine et al., 2007). As sufficient health and economic data were not available for all air pollution-related diseases, the study only considered asthma and cancer. The estimate of the overall cost of asthma and cancer treatments attributable to air pollution was situated between 0.3 and 1.3 billion euros. The second study dates from 2015 and was carried out by the General Commission for Sustainable Development and sought to assess as comprehensively as possible the cost of air pollution to the French health care system (Rafenberg, 2015). However, the study only covers a selection of pathologies (cost of treatment of respiratory diseases (asthma, acute bronchitis, chronic bronchitis, chronic obstructive pulmonary disease), respiratory cancers, and hospitalisations for respiratory and cardiovascular causes related to ambient air pollution). The study arrives at an overall cost of between 0.9 billion euros and 1.8 billion euros per year which is smaller than my estimate of the effects of a 1 $\mu g/m^3$ change in air pollution levels. In addition, these studies estimate the health care costs with great uncertainty as they apply an estimate of the fraction of these diseases that is attributable to air pollution (relative to the total incidence) and then multiply the number of disease incidence by an average of the expected treatment costs.

The report by Amann et al. (2017) discussed above also includes an estimation of health care costs linked to air pollution which is estimated at €4.7 billion per year for the

[15] In French the "Commission d'enquête sur le coût économique et financier de la pollution de l'air". `http://www.senat.fr/rap/r14-610-1/r14-610-11.pdf`

scenario of 2005 pollution levels and €2.3 billion per year for the scenario of compliance with the National Emission Reduction Commitments Directive *for the European Union (EU28) as a whole*. The benefit in terms of reduced health care costs at EU level is therefore estimated at only €2.4 billion per year which is much smaller than the benefits that I estimate for France alone. The total reduction in NO2 concentrations by 8.75 $\mu g/m^3$ from 2005 pollution levels in should allow savings of €14 billion annually in France alone.[16] The health care costs are estimated by using dose response estimates from the epidemiological literature for a selection of health effects for which evidence has been conclusive. Emerging evidence on a number of possible additional health impacts that could have major added costs such as dementia, diabetes and obesity are not considered. It is therefore not surprising that the health effects estimated in Amann et al. (2017) are much smaller than the effects presented in the present study. In a study relying similarly on dose response estimates, Pimpin et al. (2018) estimate that a 1 $\mu g/m^3$ reduction in population exposure to PM2.5 and NO2 would result in £1.42 billion and £353.3 million avoided, respectively, in NHS and social care costs between 2017 and 2035. This corresponds to a saving of only £98.5 million per year in a population of comparable size to that of France (the UK population is 66.65 million compared to 67.06 million in France in 2019). This is again much lower than the estimated effects in the present study. Again, the costs are likely underestimated because only a limited number of health conditions have been considered (asthma, COPD, coronary heart disease, stroke, type 2 diabetes, dementia and lung cancer).

While these studies clearly state that the health care cost estimates are conservative, the extent to which total effects have been underestimated has been unknown. My estimates allow to put into perspective by just how much total health care costs have been underestimated to date. Other studies that quantify health care costs are limited to relatively narrow geographical areas and time periods and/or consider only a specific part of the population (Deryugina et al., 2019; Castro et al., 2017). The estimates from these studies are therefore even more difficult to compare to the results from this study.

## *6.3. Limitations*

While the data on health care reimbursements from the French National System of Health Data provides a great detail of information concerning health care on the nature of medical acts and associated costs of treatment for all types of health care and some basic

[16]France has a population of 67 million which is about 13% of the total EU population (513). Source: Eurostat

information on patient characteristics, it does not include any information on patient socioeconomic status. The level of education, income and socioprofessional category have been proven to influence health care consumption and health status. It is important to remember that the postcode fixed effects and the IV strategy should avoid bias that could arise from residential sorting by socioeconomic status and non-random exposure to air pollution. In addition, I make some inferences about socioeconomic status based on whether the individual qualifies for free public complementary health insurance and I analyse effect heterogeneity by location characteristics as proxy for certain population characteristics. Nevertheless, this does not allow me to satisfactorily study the differences in effects according to socioeconomic status.

Another issue is the lack of clinical information, especially for certain risk factors such as smoking, weight, or body mass index.As long as daily variations in air pollution are not systematically correlated with individual smoking or drinking behaviour (controlling for day of the week FE), this should not lead to bias in my estimates. Adapting behaviours such as staying indoors and avoiding sports on high pollution days could, however, lead to an underestimate of the health costs associated with pollution exposure. Finally, I do not observe any health care consumption that would not have been subject to an insurance reimbursement. Neither self-medication nor the consumption of prescribed but not reimbursed drugs can be measured. This could again lead to an underestimation of the total effects. My estimates should therefore be considered a lower bound.

I implicitly assume that the place of residence as reported in the health care data set corresponds to the usual place where the individual is exposed to pollution. However, it is quite possible for individuals to be exposed to different concentrations of pollution than where they officially live, for example while they are at work or while travelling. I observe only the most recent place of residence and do not observe whether individuals have moved in the past.[17] This should hopefully concern only a small fraction of the sample but pollution exposure is likely to be wrongly assigned for this group and could lead my estimates to be biased toward zero (attenuation bias).

Finally, this study only considers the health care costs of short-term exposure to air pollution. While I find that these costs are sizeable enough to motivate further reduction in air pollution concentrations, the effects of chronic exposure to air pollution may be even

[17] The only information that could possibly identify whether individuals have moved is the change of affiliation to the primary health insurance fund (CPAM). There are only 102 CPAMs in metropolitan France, which means that identifying moves from changes in CPAM is clearly not sufficient to detect moves at a sufficiently fine geographic resolution.

more important in terms of overall public health relevance (Pope III et al., 2009) and merit further investigation.

## *6.4. Policy recommendation*

A review of EU rules is currently underway. One of the policy changes being discussed is a closer alignment of EU air quality standards with scientific knowledge, including the latest recommendations of the World Health Organization (WHO).[18] This planned revision is a step in the good direction. While the WHO limit values are not more stringent than the current EU framework for NO2 and O3, the revision would result in a reduction of the limit values for PM10 from an annual average of 40 $\mu g/m^3$ to 20 $\mu g/m^3$ for PM2.5 from 25 $\mu g/m^3$ to 10 $\mu g/m^3$. However, this study provides evidence for sizeable health care costs caused by levels of air pollution that are relatively low. The average PM10 concentration in the data used for this study is only $16.61 \mu g/m^3$ and the PM2.5 concentration is $10.58 \mu g/m^3$, which is below and close to the proposed new limit values, respectively. This suggests that an even stricter regulation than that of the WHO could avoid significant costs to health care systems. In addition to cost-benefit considerations, another argument for air pollution reduction is a concern for equity. The study provides evidence for significant heterogeneity of effects across patient characteristics and postcode areas, indicating that air pollution reduction policies have the potential to reduce health inequalities.

[18] `https://ec.europa.eu/environment/air/quality/revision_of_the_aaq_directives.htm`

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Table A1: Summary of the main French Air Quality Standard values

| Pollutants | Limit value | Quality objectives | Recommendation & info. threshold | Alert threshold |
|---|---|---|---|---|
| Nitrogen dioxide (NO2) | Annual mean: $40\mu g/m^3$. Hourly mean: $200\mu g/m^3$ not to be exceeded more than 18 per year. | Annual mean: $40\mu g/m^3$. | Hourly mean: $200\mu g/m^3$. | Hourly mean: $400\mu g/m^3$ exceeded on 3 consecutive hours. $200\mu g/m^3$ if the information level has already been reached the day before and the current day, and if a new exceedance is forecasted for the next day. |
| Sulphur dioxide (SO2) | Hourly mean: $125\mu g/m^3$ not to be exceeded more than 3 per year. Daily mean: $350\mu g/m^3$ not to be exceeded more than 24 per year. | Annual mean: $50\mu g/m^3$. | Hourly mean: $300\mu g/m^3$. | Hourly mean $500\mu g/m^3$ exceeded on 3 consecutive hours. |
| Particles with a diameter of $10\mu m$ or less (PM10) | Annual mean: $40\mu g/m^3$. Hourly mean: $50\mu g/m^3$ not to be exceeded more than 35 per year | Annual mean: $30\mu g/m^3$. | Daily mean: $50\mu g/m^3$. | Daily mean: $80\mu g/m^3$. |
| Carbon monoxide (CO) | Maximum daily on a 8-hour mean: $10000\mu g/m^3$. | | | |
| Ozone (O3) | | Maximum daily eight-hour mean: $120\mu g/m^3$ per civil year. | Hourly mean: $180\mu g/m^3$. | Alert threshold, hourly mean: $240\mu g/m^3$ per hour. Alert threshold for emergency measures, hourly means: 1st threshold: $> 240\mu g/m^3$ during 3 consecutive hours. 2nd threshold: $> 300\mu g/m^3$ during 3 consecutive hours. 3rd threshold: $> 360\mu g/m^3$. |
| Particles with a diameter of $2.5\mu m$ or less (PM2.5) | Annual mean: $27\mu g/m^3$ decreasing every year by equal annual percentage to reach $25\mu g/m^3$ by 2015. | Annual mean: $10\mu g/m^3$. | | |

*Source*: Airparif, `https://www.airparif.asso.fr/en/reglementation/normes-francaises`
Limit value: a level set on the basis of scientific knowledge with the aim of avoiding, preventing or reducing harmful effects on human health and/or the environment as a whole, to be attained within a given period and not to be exceeded once attained. Target value: a level fixed with the aim of avoiding, preventing or reducing harmful effects on human health and/or the environment as a whole, to be attained where possible over a given period. Quality objectives: long-term level to achieve and maintain, except where this is not achievable through proportionate measures to ensure effective protection of human health and the environment as a whole. Information threshold: a level beyond which there is a risk to human health from brief exposure for particularly sensitive sections of the population and for which immediate and appropriate information is necessary. Alert threshold: a level beyond which there is a risk to human health from brief exposure for the population as a whole and at which immediate steps are to be taken by the Member States.

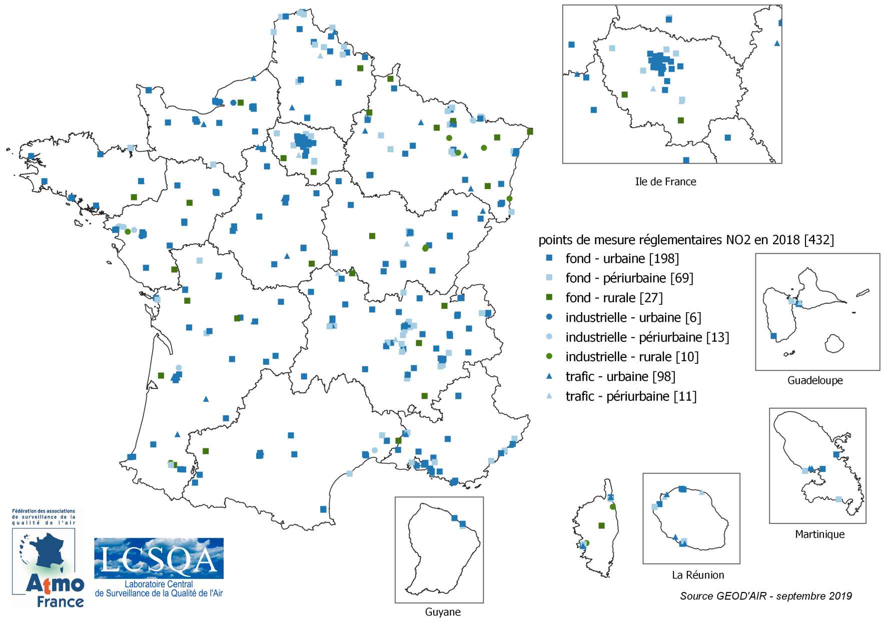


Figure A1.Map of the spatial distribution of NO2 measuring stations in France. *Source: GEOD'AIR available* here.

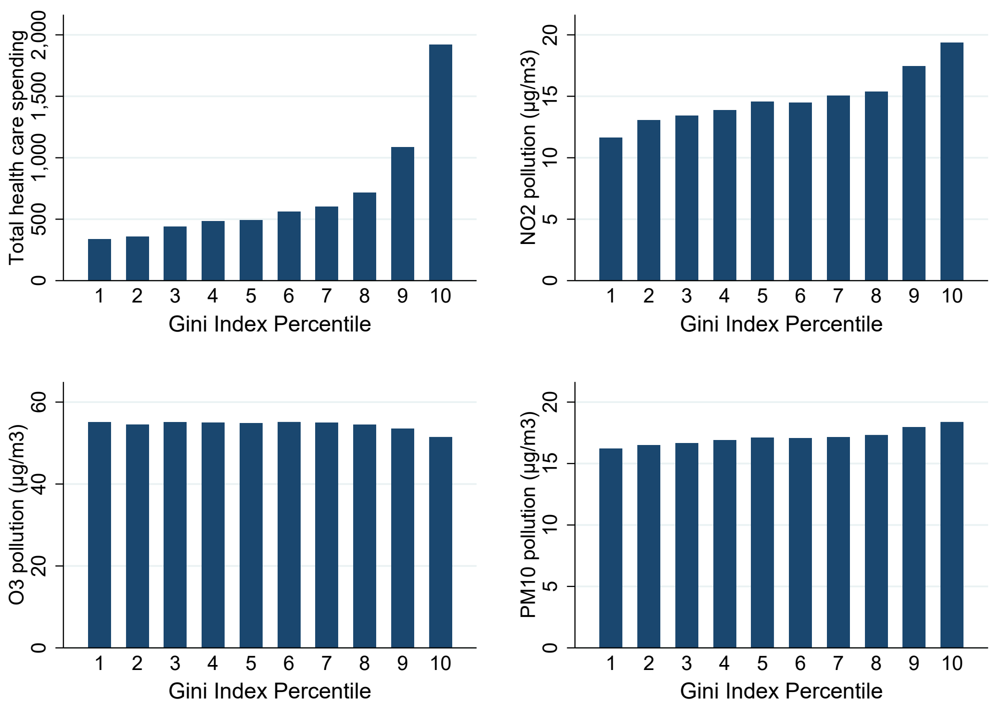


Figure A2.Mean of health care spending and pollutants by postcode area Gini Index deciles.

Table A2: Summary statistics - pooled postcode-day observations, entire sample

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| *Health care spending* | | | | | |
| Total spent | 513.76 | 1415.4 | 0 | 351206.91 | 8835995 |
| Family medicine | 172.56 | 508.53 | 0 | 71455.65 | 8836033 |
| Cardiology and vascular medicine | 7.25 | 50.75 | 0 | 37072.16 | 8836120 |
| Otorhinolaryngology | 2.75 | 23.37 | 0 | 10190 | 8836122 |
| Pneumology | 3.24 | 50.18 | 0 | 15664.6 | 8836126 |
| Ophtalmology | 11.73 | 64.19 | 0 | 6871.2 | 8836120 |
| Neurology | 2.8 | 46.1 | 0 | 10373.22 | 8836127 |
| Trauma surgery | 5.13 | 55.31 | 0 | 14687.84 | 8836114 |
| Ambulance services | 10.9 | 84.32 | 0 | 9434.66 | 8836112 |
| Gynecology | 6.15 | 41.46 | 0 | 6838.82 | 8836121 |
| Gastroenterology and hepatology | 4.61 | 111.49 | 0 | 26010.53 | 8836126 |
| Rheumatology | 4.07 | 48.72 | 0 | 11414.56 | 8836127 |
| Stomatology | 0.83 | 23.83 | 0 | 23800 | 8836126 |
| Dental surgery | 39.44 | 233.53 | 0 | 33874.4 | 8836111 |
| Nephrology | 1.63 | 24.86 | 0 | 11234.26 | 8836127 |
| Plastic surgery | 0.74 | 27.69 | 0 | 6321.91 | 8836128 |
| *Pollution measures* | | | | | |
| NO2 emission (daily mean, µg/m3) | 13.8 | 8.44 | 0.09 | 138.44 | 8761974 |
| PM 10 emission (daily mean, µg/m3) | 16.61 | 8.47 | 1.12 | 123.7 | 8761974 |
| PM 2.5 emission (daily mean, µg/m3) | 10.58 | 7.44 | 0.32 | 104.97 | 8755985 |
| O3 emission (daily mean, µg/m3) | 55.64 | 20.32 | 0 | 155.64 | 8761974 |
| *Meteorological conditions* | | | | | |
| Temperature (daily mean, °C) | 12.5 | 6.73 | -19.4 | 34.6 | 8836128 |
| Precipitation (daily sum, mm) | 2.01 | 4.60 | 0 | 150.6 | 8836128 |
| Wind speed (daily mean at 10m, m/s) | 3.11 | 1.7 | 0 | 29.6 | 8836128 |
| *Strike measures* | | | | | |
| Strike at postcode area level = 1 | 0 | 0.02 | 0 | 1 | 8836128 |
| Duration of strike at postcode area level | 33.51 | 29.76 | 1 | 108 | 4664 |
| Distance to nearest postcode area with strike | 389.21 | 218.74 | 0 | 1326 | 5757696 |
| Strike at department level = 1 | 0.04 | 0.19 | 0 | 1 | 8836128 |
| Duration of strike at department level | 13.13 | 10.88 | 1 | 43 | 339148 |
| Strike at national level = 1 | 0.25 | 0.44 | 0 | 1 | 8836128 |
| Duration of strike at national level | 56.08 | 27.06 | 1 | 87 | 2249856 |
| Percentage of SNCF personnel striking | 5.4 | 4.2 | 0.2 | 11.5 | 1149120 |
| Strike at any geographical level = 1 | 0.29 | 0.45 | 0 | 1 | 8836128 |
| *Postcode characteristics* | | | | | |
| Income | 22096.28 | 4050.53 | 7910 | 52670 | 8790837 |
| Unemployment rate | 2.88 | 0.73 | 1 | 7.5 | 5744652 |
| Gini index | 0.32 | 0.05 | 0.21 | 0.63 | 5744652 |

Table A3: Summary statistics - pooled postcode-day observations, 10% most densely populated areas

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| *Health care spending* | | | | | |
| Total spent | 2162.65 | 3373.44 | 0 | 351206.91 | 882437 |
| Family medicine | 716.32 | 1155.77 | 0 | 71455.65 | 882436 |
| Cardiology and vascular medicine | 32.11 | 117.7 | 0 | 37072.16 | 882437 |
| Otorhinolaryngology | 12.47 | 52.36 | 0 | 10190 | 882441 |
| Pneumology | 13.73 | 113.19 | 0 | 15664.6 | 882444 |
| Ophtalmo. | 48.84 | 138.98 | 0 | 6871.2 | 882439 |
| Neurology | 11.29 | 86.31 | 0 | 6324.41 | 882444 |
| Trauma surgery | 19.04 | 111.7 | 0 | 14687.84 | 882442 |
| Ambulance services | 44.33 | 185.62 | 0 | 7159.73 | 882437 |
| Gynecology | 28.77 | 98.74 | 0 | 6838.82 | 882443 |
| Gastroenterology and hepatology | 20.77 | 256.75 | 0 | 25730.96 | 882442 |
| Rheumatology | 16.29 | 82.7 | 0 | 5842.46 | 882444 |
| Stomatology | 4 | 58.05 | 0 | 23800 | 882443 |
| Dental surgery | 170.33 | 522.71 | 0 | 33874.4 | 882438 |
| Nephrology | 8.27 | 54.38 | 0 | 9168.77 | 882443 |
| Plastic surgery | 3.46 | 62.49 | 0 | 6321.91 | 882444 |
| *Pollution measures* | | | | | |
| NO2 emission (daily mean, µg/m3) | 19.47 | 11.83 | 1.13 | 138.44 | 877330 |
| PM 10 emission (daily mean, µg/m3) | 18.23 | 9.52 | 1.75 | 123.7 | 877330 |
| PM 2.5 emission (daily mean, µg/m3) | 11.61 | 8.23 | 0.79 | 104.97 | 876730 |
| O3 emission (daily mean, µg/m3) | 51.24 | 21.95 | 0 | 149.24 | 877330 |
| *Meteorological conditions* | | | | | |
| Temperature (daily mean, °C) | 13.05 | 6.76 | -10.5 | 34.6 | 882444 |
| Precipitation (daily sum, mm) | 1.87 | 4.46 | 0 | 132.3 | 882444 |
| Wind speed (daily mean at 10m, m/s) | 3.17 | 1.63 | 0 | 18.3 | 882444 |
| *Strike measures* | | | | | |
| Strike at postcode area level = 1 | 0 | 0.07 | 0 | 1 | 882444 |
| Duration of strike at postcode area level | 34.83 | 30.55 | 1 | 108 | 4277 |
| Distance to nearest postcode area with strike | 378.83 | 215.31 | 0 | 1264 | 575008 |
| Strike at department level = 1 | 0.05 | 0.22 | 0 | 1 | 882444 |
| Duration of strike at department level | 13 | 10.54 | 1 | 43 | 47115 |
| Strike at national level = 1 | 0.25 | 0.44 | 0 | 1 | 882444 |
| Duration of strike at national level | 56.08 | 27.06 | 1 | 87 | 224688 |
| Percentage of SNCF personnel striking | 5.4 | 4.2 | 0.2 | 11.5 | 114760 |
| Strike at any geographical level = 1 | 0.3 | 0.46 | 0 | 1 | 882444 |
| *Postcode characteristics* | | | | | |
| Income | 22706.29 | 5613.86 | 7910 | 52670 | 880983 |
| Unemployment rate | 3.14 | 0.83 | 1 | 7.5 | 880983 |
| Gini index | 0.37 | 0.06 | 0.25 | 0.63 | 880983 |

Table A4: Summary statistics - pooled postcode-day observations, sample of 70 biggest cities

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| *Health care spending* | | | | | |
| Total spent | 3550.97 | 5391.95 | 0 | 351206.91 | 241065 |
| Family medicine | 1152.02 | 1703.38 | 0 | 40544.62 | 241065 |
| Cardiology and vascular medicine | 55.57 | 157.88 | 0 | 8241.84 | 241058 |
| Otorhinolaryngology | 21.19 | 76.37 | 0 | 10190 | 241064 |
| Pneumology | 21.68 | 133.34 | 0 | 7250.7 | 241065 |
| Ophtalmology | 78.04 | 192.76 | 0 | 5376.22 | 241062 |
| Neurology | 19.28 | 120 | 0 | 5481.27 | 241065 |
| Trauma surgery | 28.04 | 143.88 | 0 | 6950.02 | 241063 |
| Ambulance services | 70.61 | 246.44 | 0 | 6859.2 | 241063 |
| Gynecology | 51.14 | 145.08 | 0 | 6838.82 | 241065 |
| Gastroenterology and hepatology | 35.61 | 364.4 | 0 | 25730.96 | 241064 |
| Rhumatology | 27.57 | 108.32 | 0 | 5842.46 | 241065 |
| Stomatology | 6.83 | 84.44 | 0 | 23800 | 241064 |
| Dental surgery | 283.48 | 738.01 | 0 | 33874.4 | 241064 |
| Nephrology | 14.78 | 75.93 | 0 | 9168.77 | 241064 |
| Plastic surgery. | 6.18 | 79.91 | 0 | 5326.77 | 241065 |
| *Pollution measures* | | | | | |
| NO2 emission (daily mean, µg/m3) | 22.87 | 12.86 | 1.28 | 138.44 | 237412 |
| PM 10 emission (daily mean, µg/m3) | 19.28 | 9.89 | 1.87 | 123.7 | 237412 |
| PM 2.5 emission (daily mean, µg/m3) | 12.18 | 8.39 | 0.79 | 104.97 | 237250 |
| O3 emission (daily mean, µg/m3) | 50.21 | 22.57 | 0 | 142.47 | 237412 |
| *Meteorological conditions* | | | | | |
| Temperature (daily mean, °C) | 13.54 | 6.75 | -8.1 | 34.6 | 241065 |
| Precipitation (daily sum, mm) | 1.8 | 4.47 | 0 | 132.3 | 241065 |
| Wind speed (daily mean at 10m, m/s) | 3.26 | 1.71 | 0 | 18.3 | 241065 |
| *Strike measures* | | | | | |
| Strike at postcode area level = 1 | 0.02 | 0.13 | 0 | 1 | 241065 |
| Duration of strike at postcode area level | 32.52 | 28.9 | 1 | 108 | 3933 |
| Distance to nearest postcode area with strike | 388.97 | 224.93 | 0 | 1257 | 157080 |
| Strike at department level = 1 | 0.05 | 0.23 | 0 | 1 | 241065 |
| Duration of strike at department level | 12.87 | 10.32 | 1 | 35 | 12904 |
| Strike at national level = 1 | 0.25 | 0.44 | 0 | 1 | 241065 |
| Duration of strike at national level | 56.08 | 27.06 | 1 | 87 | 61380 |
| Percentage of SNCF personnel striking | 5.4 | 4.2 | 0.2 | 11.5 | 31350 |
| Strike at any geographical level = 1 | 0.31 | 0.46 | 0 | 1 | 241065 |
| *Postcode characteristics* | | | | | |
| Income | 22318.8 | 7189.22 | 7910 | 50570 | 241065 |
| Unemployment rate | 3.31 | 0.96 | 1 | 7.5 | 241065 |
| Gini index | 0.43 | 0.05 | 0.33 | 0.63 | 241065 |

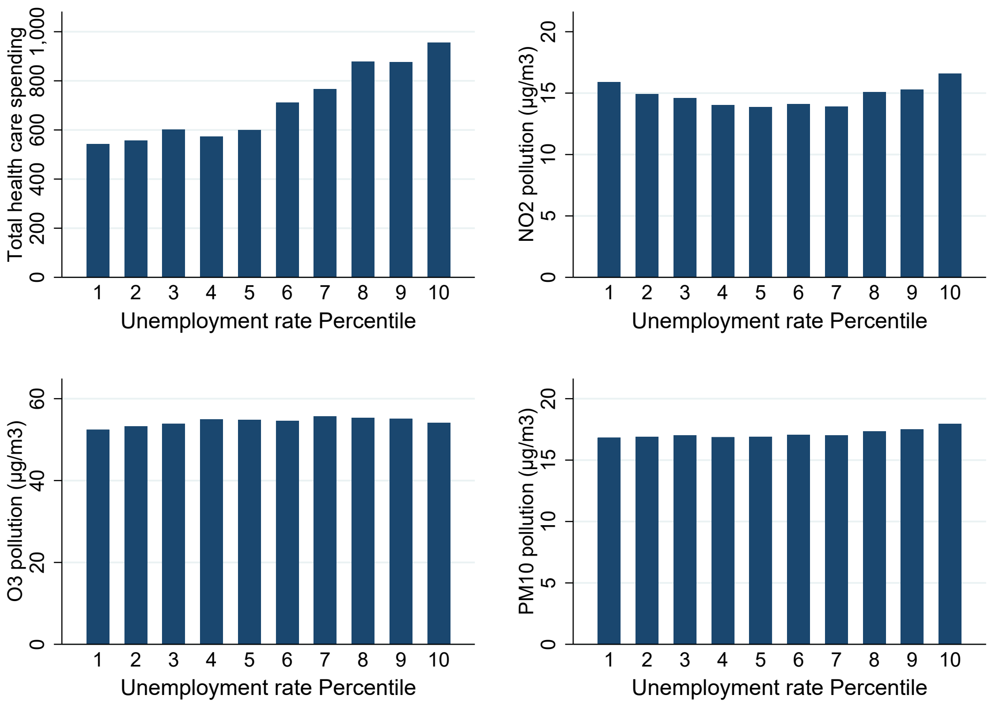


Figure A3.Mean of health care spending and pollutants by postcode area unemployment rate deciles.

Table A5: OLS and IV Estimates of Effect of NO2 and O3 on Health Care Expenditure

| | Spending - 10% most populated areas | | |
|---|---|---|---|
| | OLS<br>(1) | Wind IV<br>(2) | Strike IV<br>(3) |
| NO2 mean | 9.951*** | 23.98*** | 105.8*** |
| | (1.129) | (3.726) | (25.456) |
| Effect relative to mean (%) | 0.5 | 1.1 | 4.9 |
| O3 mean | 2.607*** | 17.88*** | 103.6*** |
| | (0.282) | (2.487) | (17.050) |
| Effect relative to mean (%) | 0.1 | 0.8 | 4.8 |
| Constant | -99.09 | | |
| | (123.356) | | |
| Dependent variable mean | 2162.65 | 2162.65 | 2162.65 |
| Observations | 837876 | 836730 | 637450 |
| First-stage F-stat | | 1356.1 | 424.8 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, department-month, month-year and postcode fixed effects.

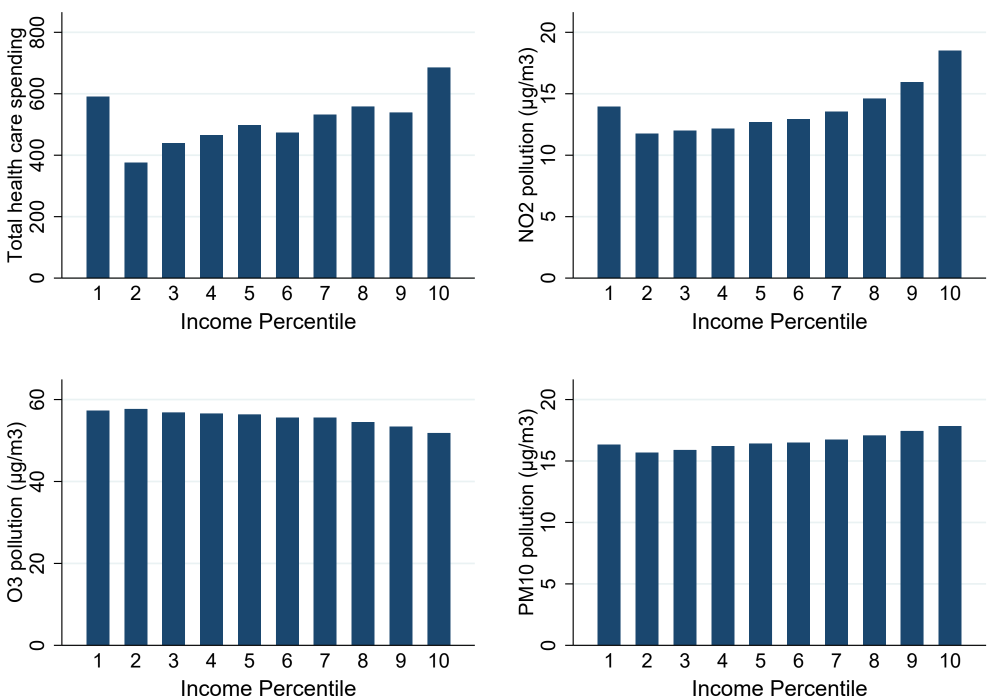


Figure A4.Mean of health care spending and pollutants by postcode area income deciles.

Table A6: First stage regressions corresponding to the IV regressions shown in Table 1 for the sample of the 70 biggest cities

| | NO2 mean | O3 mean | PM 10 mean | NO2 mean | O3 mean | PM 10 mean |
|---|---|---|---|---|---|---|
| Low wind speed | 7.131*** | -8.136*** | 3.193*** | | | |
| | (0.177) | (0.201) | (0.108) | | | |
| Low wind speed lag 1 | 2.488*** | -4.708*** | 2.699*** | | | |
| | (0.091) | (0.124) | (0.099) | | | |
| Low wind speed lag 2 | 0.125*** | -1.306*** | 1.069*** | | | |
| | (0.029) | (0.081) | (0.044) | | | |
| Strike day 1 | | | | 0.274*** | 0.147 | -0.258*** |
| | | | | (0.076) | (0.093) | (0.058) |
| Strike day 2 | | | | 1.645*** | -1.732*** | 0.260 |
| | | | | (0.076) | (0.159) | (0.132) |
| Strike day 3 | | | | 1.206*** | -2.681*** | -0.403*** |
| | | | | (0.114) | (0.188) | (0.114) |
| Constant | 15.53*** | 73.92*** | 12.63*** | 20.14*** | 68.97*** | 15.39*** |
| | (0.385) | (0.560) | (0.488) | (0.429) | (0.579) | (0.514) |
| Observations | 215203 | 215203 | 215203 | 162491 | 162491 | 162491 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A7: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area Gini Index quintiles (whole sample)

*OLS regression, heterogeneity by Gini Index quintile (1st quintile is most equal)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 1.255*** | 2.394*** | 2.174*** | 4.581*** | 13.09*** |
| | (0.220) | (0.310) | (0.361) | (0.496) | (1.374) |
| Effect relative to mean (%) | 0.36 | 0.52 | 0.41 | 0.70 | 0.87 |
| O3 mean | 0.0906 | 0.468*** | 0.351*** | 0.596*** | 2.304*** |
| | (0.062) | (0.095) | (0.103) | (0.120) | (0.303) |
| Effect relative to mean (%) | 0.03 | 0.10 | 0.07 | 0.09 | 0.15 |
| Constant | 35.50** | 30.00 | 34.11 | 1.282 | 22.23 |
| | (13.034) | (19.061) | (20.203) | (31.029) | (103.696) |
| Dependent variable mean | 349.3 | 461.02 | 526.54 | 658.89 | 1505.1 |
| Observations | 1155743 | 1084711 | 1114222 | 1071969 | 1031174 |

*Wind IV regression, heterogeneity by Gini Index quintile (1st quintile is most equal)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 5.386** | 9.364*** | 4.940* | 9.412*** | 20.08*** |
| | (2.004) | (2.570) | (2.419) | (2.781) | (3.998) |
| Effect relative to mean (%) | 1.5 | 2.0 | 0.9 | 1.4 | 1.3 |
| O3 mean | 2.423** | 4.872*** | 3.056* | 5.643*** | 14.42*** |
| | (0.892) | (1.216) | (1.280) | (1.512) | (2.602) |
| Effect relative to mean (%) | 0.7 | 1.1 | 0.6 | 0.9 | 1.0 |
| Dependent variable mean | 349.3 | 461.02 | 526.54 | 658.89 | 1505.1 |
| Observations | 1157331 | 1086203 | 1115756 | 1073445 | 1032594 |
| First-stage F-stat | 1877.0 | 1462.5 | 1572.2 | 1397.7 | 1479.6 |

*Strike IV regression, heterogeneity by Gini Index quintile (1st quintile is most equal)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 20.65*** | 14.96*** | 21.80*** | 29.90*** | 52.13*** |
| | (4.314) | (4.205) | (4.824) | (4.737) | (8.566) |
| Effect relative to mean (%) | 5.9 | 3.2 | 4.1 | 4.5 | 3.5 |
| O3 mean | 5.256* | 15.59*** | 20.66*** | 14.67*** | 32.49*** |
| | (2.457) | (3.855) | (3.813) | (3.677) | (6.833) |
| Effect relative to mean (%) | 1.5 | 3.4 | 3.9 | 2.2 | 2.2 |
| Dependent variable mean | 349.3 | 461.02 | 526.54 | 658.89 | 1505.1 |
| Observations | 1158917 | 1087691 | 1117284 | 1074915 | 1034008 |
| First-stage F-stat | 501.2 | 403.3 | 461.3 | 457.4 | 502.2 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, month-by-department, month-by-year and postcode fixed effects.

Table A8: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area unemployment quintiles (whole sample)

*OLS regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 6.467*** | 5.286*** | 5.593*** | 9.589*** | 10.85*** |
| | (1.104) | (1.126) | (0.744) | (1.960) | (1.218) |
| Effect relative to mean (%) | 1.2 | 0.9 | 0.9 | 1.2 | 1.2 |
| O3 mean | 1.025*** | 0.737*** | 0.916*** | 1.259*** | 1.387*** |
| | (0.178) | (0.179) | (0.155) | (0.324) | (0.213) |
| Effect relative to mean (%) | 0.19 | 0.13 | 0.14 | 0.16 | 0.15 |
| Constant | 37.89 | 49.39 | 10.60 | -11.84 | 56.45 |
| | (29.548) | (29.289) | (34.872) | (76.235) | (59.862) |
| Dependent variable mean | 549.83 | 583.04 | 634.71 | 804.82 | 915.47 |
| Observations | 1312723 | 998753 | 976175 | 1118594 | 1051574 |

*Wind IV regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 6.142*** | 12.60*** | 10.77** | 10.23* | 8.902* |
| | (1.827) | (2.628) | (3.420) | (4.771) | (3.715) |
| Effect relative to mean (%) | 1.1 | 2.2 | 1.7 | 1.3 | 1.0 |
| O3 mean | 3.512*** | 7.066*** | 5.933*** | 6.036* | 5.761** |
| | (0.951) | (1.342) | (1.632) | (2.508) | (2.215) |
| Effect relative to mean (%) | 0.6 | 1.2 | 0.9 | 0.7 | 0.6 |
| Dependent variable mean | 549.83 | 583.04 | 634.71 | 804.82 | 915.47 |
| Observations | 1314531 | 1000127 | 977515 | 1120134 | 1053022 |
| First-stage F-stat | 1528.6 | 1140.1 | 1150.9 | 1348.6 | 1604.3 |

*Strike IV regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 20.93*** | 26.74*** | 24.17*** | 34.52*** | 44.88*** |
| | (4.933) | (5.357) | (6.133) | (7.786) | (6.747) |
| Effect relative to mean (%) | 3.8 | 4.6 | 3.8 | 4.3 | 4.9 |
| O3 mean | 15.69*** | 15.49*** | 9.346* | 19.35*** | 26.24*** |
| | (3.272) | (3.918) | (4.362) | (5.336) | (5.448) |
| Effect relative to mean (%) | 2.9 | 2.7 | 1.5 | 2.4 | 2.9 |
| Dependent variable mean | 549.83 | 583.04 | 634.71 | 804.82 | 915.47 |
| Observations | 1316331 | 1001497 | 978855 | 1121668 | 1054464 |
| First-stage F-stat | 537.1 | 393.4 | 340.5 | 450.9 | 584.0 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, month-by-department, month-by-year and postcode fixed effects.

Table A9: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area income quintiles (whole sample)

*OLS regression, heterogeneity by income quintile (1st quintile is lowest income)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 10.67*** | 7.607*** | 6.705*** | 5.383*** | 5.968*** |
| | (1.178) | (1.407) | (1.535) | (0.933) | (0.813) |
| Effect relative to mean (%) | 2.21 | 1.68 | 1.38 | 0.99 | 0.97 |
| O3 mean | 0.981*** | 0.873*** | 0.763*** | 0.596*** | 1.055*** |
| | (0.158) | (0.172) | (0.213) | (0.141) | (0.149) |
| Effect relative to mean (%) | 0.20 | 0.19 | 0.16 | 0.11 | 0.17 |
| Constant | 25.02 | 5.155 | 13.98 | 28.98 | 41.71 |
| | (38.252) | (38.465) | (36.828) | (28.646) | (30.022) |
| Dependent variable mean | 482.9 | 451.93 | 485.6 | 545.4 | 612.6 |
| Observations | 1723605 | 1685361 | 1693730 | 1664954 | 1664227 |

*Wind IV regression, heterogeneity by income quintile (1st quintile is lowest income)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 4.973 | 1.691 | 11.58** | 9.599*** | 8.523*** |
| | (3.871) | (3.207) | (3.635) | (2.743) | (1.566) |
| Effect relative to mean (%) | 1.0 | 0.4 | 2.4 | 1.8 | 1.4 |
| O3 mean | 2.327 | 1.171 | 5.422*** | 4.948*** | 5.483*** |
| | (1.713) | (1.280) | (1.589) | (1.330) | (0.941) |
| Effect relative to mean (%) | 0.5 | 0.3 | 1.1 | 0.9 | 0.9 |
| Dependent variable mean | 482.9 | 451.93 | 485.6 | 545.4 | 612.6 |
| Observations | 1725977 | 1687673 | 1696064 | 1667250 | 1666513 |
| First-stage F-stat | 1519.9 | 1743.7 | 2037.9 | 2399.4 | 3580.4 |

*Strike IV regression, heterogeneity by income quintile (1st quintile is lowest income)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 18.15*** | 21.19*** | 25.61*** | 22.36*** | 23.40*** |
| | (4.857) | (5.259) | (5.688) | (4.149) | (4.248) |
| Effect relative to mean (%) | 3.8 | 4.7 | 5.3 | 4.1 | 3.8 |
| O3 mean | 14.68*** | 7.036* | 10.22*** | 16.47*** | 17.77*** |
| | (3.902) | (3.209) | (2.978) | (3.344) | (2.857) |
| Effect relative to mean (%) | 3.0 | 1.6 | 2.1 | 3.0 | 2.9 |
| Dependent variable mean | 482.9 | 451.93 | 485.6 | 545.4 | 612.6 |
| Observations | 1728341 | 1689987 | 1698386 | 1669532 | 1668797 |
| First-stage F-stat | 859.7 | 782.8 | 683.8 | 663.9 | 735.2 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, month-by-department, month-by-year and postcode fixed effects.

Table A10: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area Gini Index quintiles (10% most populated postcode areas sample)

*OLS regression, heterogeneity by Gini Index quintile (1st quintile is most equal)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 3.149** | 6.132*** | 4.459*** | 13.61*** | 14.84*** |
| | (0.995) | (1.170) | (1.307) | (2.569) | (3.326) |
| Effect relative to mean (%) | 0.24 | 0.37 | 0.22 | 0.58 | 0.42 |
| O3 mean | 0.623 | 1.606*** | 0.910 | 3.267*** | 4.155*** |
| | (0.396) | (0.411) | (0.523) | (0.809) | (1.064) |
| Effect relative to mean (%) | 0.05 | 0.10 | 0.05 | 0.14 | 0.12 |
| Constant | 139.9* | -57.02 | 15.02 | 221.4 | -25.50 |
| | (67.603) | (105.923) | (127.333) | (227.060) | (493.321) |
| Dependent variable mean | 1324.9 | 1654.3 | 1996.2 | 2357.6 | 3511.9 |
| Observations | 174838 | 167554 | 174474 | 157355 | 159902 |

*Wind IV regression, heterogeneity by Gini Index quintile (1st quintile is most equal)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 21.96*** | 20.33*** | 24.18*** | 26.23** | 27.69* |
| | (6.646) | (6.054) | (6.452) | (8.145) | (11.043) |
| Effect relative to mean (%) | 1.7 | 1.2 | 1.2 | 1.1 | 0.8 |
| O3 mean | 13.11*** | 13.57*** | 19.33*** | 18.68*** | 26.04** |
| | (3.418) | (3.710) | (4.618) | (5.338) | (8.997) |
| Effect relative to mean (%) | 1.0 | 0.8 | 1.0 | 0.8 | 0.7 |
| Dependent variable mean | 1324.9 | 1654.3 | 1996.2 | 2357.6 | 3511.9 |
| Observations | 175078 | 167784 | 174712 | 157571 | 160126 |
| First-stage F-stat | 287.8 | 233.5 | 340.6 | 247.4 | 442.9 |

*Strike IV regression, heterogeneity by Gini Index quintile (1st quintile is most equal)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 66.80** | 91.36** | 71.13* | 155.0*** | 183.0*** |
| | (25.557) | (29.383) | (31.713) | (35.218) | (42.606) |
| Effect relative to mean (%) | 5.0 | 5.5 | 3.6 | 6.6 | 5.2 |
| O3 mean | 71.46 | 78.39* | 16.41 | 212.3*** | 86.93 |
| | (39.680) | (30.974) | (32.102) | (57.663) | (54.543) |
| Effect relative to mean (%) | 5.4 | 4.7 | 0.8 | 9.0 | 2.5 |
| Dependent variable mean | 1324.9 | 1654.3 | 1996.2 | 2357.6 | 3511.9 |
| Observations | 175318 | 168014 | 174952 | 157787 | 160344 |
| First-stage F-stat | 46.07 | 80.86 | 112.5 | 88.94 | 139.2 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, month-by-department, month-by-year and postcode fixed effects.

Table A11: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area unemployment quintiles (10% most populated postcode areas sample)

*OLS regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 12.54*** | 7.472*** | 11.46** | 12.75** | 9.585*** |
| | (2.575) | (2.006) | (3.618) | (3.848) | (2.115) |
| Effect relative to mean (%) | 0.60 | 0.45 | 0.54 | 0.52 | 0.39 |
| O3 mean | 2.819*** | 1.820*** | 1.916* | 2.718* | 1.868** |
| | (0.609) | (0.518) | (0.769) | (1.076) | (0.705) |
| Effect relative to mean (%) | 0.13 | 0.11 | 0.09 | 0.11 | 0.08 |
| Constant | 146.3 | 73.31 | 70.61 | -122.6 | 87.84 |
| | (164.271) | (128.023) | (280.321) | (393.927) | (273.052) |
| Dependent variable mean | 2095.4 | 1655.6 | 2122.2 | 2438.5 | 2463.3 |
| Observations | 195232 | 150433 | 165735 | 160270 | 162453 |

*Wind IV regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 24.42*** | 22.62** | 39.14*** | 17.21 | 17.47* |
| | (4.693) | (7.318) | (11.555) | (13.226) | (6.802) |
| Effect relative to mean (%) | 1.2 | 1.4 | 1.8 | 0.7 | 0.7 |
| O3 mean | 19.63*** | 14.96*** | 25.52*** | 12.32 | 15.03** |
| | (3.422) | (3.827) | (6.564) | (8.329) | (5.622) |
| Effect relative to mean (%) | 0.9 | 0.9 | 1.2 | 0.5 | 0.6 |
| Dependent variable mean | 2095.4 | 1655.6 | 2122.2 | 2438.5 | 2463.3 |
| Observations | 195500 | 150641 | 165961 | 160490 | 162679 |
| First-stage F-stat | 325.9 | 192.9 | 249.2 | 271.4 | 679.1 |

*Strike IV regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 128.8*** | 115.1*** | 97.50** | 150.2*** | 144.8*** |
| | (32.037) | (34.177) | (33.598) | (40.856) | (36.084) |
| Effect relative to mean (%) | 6.1 | 7.0 | 4.6 | 6.2 | 5.9 |
| O3 mean | 109.8*** | 151.6** | 30.90 | 94.03 | 92.29* |
| | (31.645) | (46.640) | (36.174) | (55.345) | (41.614) |
| Effect relative to mean (%) | 5.2 | 9.2 | 1.5 | 3.9 | 3.7 |
| Dependent variable mean | 2095.4 | 1655.6 | 2122.2 | 2438.5 | 2463.3 |
| Observations | 195768 | 150847 | 166189 | 160710 | 162901 |
| First-stage F-stat | 91.43 | 51.43 | 65.83 | 80.39 | 143.0 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, month-by-department, month-by-year and postcode fixed effects.

Table A12: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area income quintiles (10% most populated postcode areas sample)

*OLS regression, heterogeneity by income quintile (1st quintile is lowest income)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 5.816** | 14.46*** | 18.30** | 8.594** | 11.66*** |
| | (1.739) | (3.598) | (6.155) | (3.057) | (2.176) |
| Effect relative to mean (%) | 0.2 | 0.6 | 1.0 | 0.5 | 0.5 |
| O3 mean | 1.506 | 2.343** | 3.394** | 1.520* | 3.102*** |
| | (0.809) | (0.699) | (1.234) | (0.677) | (0.613) |
| Effect relative to mean (%) | 0.06 | 0.10 | 0.18 | 0.08 | 0.14 |
| Constant | -63.22 | 61.73 | 23.78 | 19.16 | 236.2 |
| | (327.423) | (266.431) | (304.957) | (181.253) | (179.065) |
| Dependent variable mean | 2594.0 | 2298.2 | 1843.3 | 1878.1 | 2204.6 |
| Observations | 166461 | 160269 | 170104 | 166096 | 171193 |

*Wind IV regression, heterogeneity by income quintile (1st quintile is lowest income)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 24.20** | 15.75 | 27.36* | 27.56** | 23.36*** |
| | (8.741) | (10.302) | (13.336) | (8.564) | (4.330) |
| Effect relative to mean (%) | 0.93 | 0.69 | 1.48 | 1.47 | 1.06 |
| O3 mean | 20.49** | 11.61 | 15.72* | 18.81*** | 20.98*** |
| | (6.736) | (6.160) | (6.725) | (5.163) | (3.598) |
| Effect relative to mean (%) | 0.79 | 0.51 | 0.85 | 1.00 | 0.95 |
| Dependent variable mean | 2594.0 | 2298.2 | 1843.3 | 1878.1 | 2204.6 |
| Observations | 166691 | 160489 | 170336 | 166324 | 171431 |
| First-stage F-stat | 621.3 | 194.7 | 231.7 | 250.1 | 562.9 |

*Strike IV regression, heterogeneity by income quintile (1st quintile is lowest income)*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 148.4*** | 120.4*** | 103.8** | 145.7*** | 138.1*** |
| | (38.811) | (31.661) | (38.836) | (39.259) | (32.454) |
| Effect relative to mean (%) | 5.7 | 5.2 | 5.6 | 7.8 | 6.3 |
| O3 mean | 139.8* | 77.94 | 41.67 | 118.5** | 100.5** |
| | (58.607) | (48.570) | (44.333) | (39.745) | (32.237) |
| Effect relative to mean (%) | 5.4 | 3.4 | 2.3 | 6.3 | 4.6 |
| Dependent variable mean | 2594.0 | 2298.2 | 1843.3 | 1878.1 | 2204.6 |
| Observations | 166919 | 160709 | 170570 | 166552 | 171665 |
| First-stage F-stat | 168.7 | 71.68 | 44.17 | 95.86 | 71.47 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, month-by-department, month-by-year and postcode fixed effects.

Table A13: Effects of NO2 and O3 on total health care spending - heterogeneous effects by NO2 pollution quintiles (whole sample)

*OLS regression, heterogeneity by average postcode NO2 quintile*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 2.448*** | 2.397*** | 2.241*** | 2.126*** | 6.878*** |
| | (0.284) | (0.250) | (0.266) | (0.383) | (0.654) |
| Effect relative to mean (%) | 0.8 | 0.7 | 0.6 | 0.4 | 0.6 |
| O3 mean | 0.220** | 0.270*** | 0.231** | 0.241* | 1.462*** |
| | (0.068) | (0.057) | (0.071) | (0.108) | (0.174) |
| Effect relative to mean (%) | 0.1 | 0.1 | 0.1 | 0.05 | 0.1 |
| Constant | 15.55 | -2.228 | 25.86 | 0.413 | 46.88 |
| | (11.338) | (15.458) | (18.352) | (28.003) | (63.254) |
| Dependent variable mean | 302.27 | 326.20 | 391.61 | 488.59 | 1061.75 |
| Observations | 1628872 | 1716686 | 1720701 | 1723613 | 1682801 |

*Wind IV regression, heterogeneity by average postcode NO2 quintile*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 8.298*** | 10.79*** | 7.149* | 8.046*** | 8.172*** |
| | (2.461) | (2.980) | (3.395) | (2.359) | (1.851) |
| Effect relative to mean (%) | 2.7 | 3.3 | 1.8 | 1.6 | 0.8 |
| O3 mean | 2.963*** | 4.001*** | 3.084* | 4.522*** | 6.469*** |
| | (0.791) | (1.011) | (1.441) | (1.225) | (1.308) |
| Effect relative to mean (%) | 1.0 | 1.2 | 0.8 | 0.9 | 0.6 |
| Dependent variable mean | 302.27 | 326.20 | 391.61 | 488.59 | 1061.75 |
| Observations | 1631126 | 1719044 | 1723063 | 1725979 | 1685117 |
| First-stage F-stat | 6228.4 | 7247.0 | 7936.0 | 7967.0 | 7846.2 |

*Strike IV regression, heterogeneity by average postcode NO2 quintile*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 2.089 | 23.83*** | 21.13*** | 24.83*** | 35.69*** |
| | (7.447) | (5.099) | (3.921) | (4.393) | (4.949) |
| Effect relative to mean (%) | 0.7 | 7.3 | 5.4 | 5.1 | 3.4 |
| O3 mean | 10.41*** | 1.520 | 4.816* | 13.11*** | 27.58*** |
| | (2.966) | (2.433) | (2.403) | (2.638) | (3.963) |
| Effect relative to mean (%) | 3.4 | 0.5 | 1.2 | 2.7 | 2.6 |
| Dependent variable mean | 302.27 | 326.20 | 391.61 | 488.59 | 1061.75 |
| Observations | 1633356 | 1721400 | 1725425 | 1728345 | 1687425 |
| First-stage F-stat | 1519.0 | 1773.8 | 1421.6 | 820.0 | 1130.5 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, month-by-department, month-by-year and postcode fixed effects.

Table A14: Effects of NO2 and O3 on total health care spending - heterogeneous effects by NO2 pollution quintiles (10% most populated postcode areas)

*OLS regression, heterogeneity by average postcode NO2 quintile*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 9.854*** | 8.429** | 8.963*** | 4.829** | 6.531*** |
| | (1.763) | (3.085) | (2.221) | (1.517) | (1.414) |
| Effect relative to mean (%) | 0.6 | 0.4 | 0.5 | 0.2 | 0.2 |
| O3 mean | 1.453** | 1.388 | 2.197*** | 1.614 | 3.503*** |
| | (0.451) | (0.860) | (0.553) | (0.889) | (0.638) |
| Effect relative to mean (%) | 0.09 | 0.07 | 0.12 | 0.07 | 0.11 |
| Constant | 23.90 | -6.857 | -27.16 | -64.34 | 141.6 |
| | (98.080) | (206.245) | (194.807) | (394.039) | (323.432) |
| Dependent variable mean | 1540.25 | 1971.63 | 1803.89 | 2414.08 | 3057.84 |
| Observations | 170465 | 167555 | 169011 | 159538 | 169011 |

*Wind IV regression, heterogeneity by average postcode NO2 quintile*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 49.29*** | 27.61* | 17.30 | 22.61** | 23.75*** |
| | (10.244) | (14.043) | (10.700) | (8.329) | (3.957) |
| Effect relative to mean (%) | 3.2 | 1.4 | 1.0 | 0.9 | 0.8 |
| O3 mean | 21.25*** | 16.35* | 11.45 | 21.17** | 26.30*** |
| | (3.799) | (7.060) | (6.444) | (6.552) | (4.412) |
| Effect relative to mean (%) | 1.38 | 0.83 | 0.63 | 0.88 | 0.86 |
| Dependent variable mean | 1540.25 | 1971.63 | 1803.89 | 2414.08 | 3057.84 |
| Observations | 170699 | 167785 | 169243 | 159760 | 169243 |
| First-stage F-stat | 720.2 | 732.2 | 1003.1 | 2323.7 | 4411.4 |

*Strike IV regression, heterogeneity by average postcode NO2 quintile*

| | Total spent - 1st quintile | Total spent - 2nd quintile | Total spent - 3rd quintile | Total spent - 4th quintile | Total spent - 5th quintile |
|---|---|---|---|---|---|
| NO2 mean | 45.27 | 178.3*** | 132.8*** | 107.4** | 136.5*** |
| | (88.169) | (35.451) | (37.785) | (36.894) | (37.466) |
| Effect relative to mean (%) | 2.9 | 9.0 | 7.4 | 4.4 | 4.5 |
| O3 mean | 70.74 | 68.96 | 105.0** | 41.79 | 129.1*** |
| | (53.270) | (58.881) | (35.079) | (48.864) | (34.000) |
| Effect relative to mean (%) | 4.6 | 3.5 | 5.82 | 1.7 | 4.2 |
| Dependent variable mean | 1540.25 | 1971.63 | 1803.89 | 2414.08 | 3057.84 |
| Observations | 170933 | 168015 | 169475 | 159978 | 169475 |
| First-stage F-stat | 72.24 | 82.21 | 72.13 | 130.0 | 241.1 |

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note: Robust standard errors clustered at the postcode level in parenthesis.

All models include day of the week, day of the month, month and postcode fixed effects.

Table A15: Impact of pollution on health care expenditure by age, OLS model (entire sample)

| | Age 0 to 10 | Age 11 to 20 | Age 21 to 30 | Age 31 to 40 | Age 41 to 50 |
|---|---|---|---|---|---|
| NO2 mean | 0.493*** | 0.578*** | 0.284*** | 0.685*** | 0.892*** |
| | (0.035) | (0.048) | (0.032) | (0.060) | (0.064) |
| Effect relative to mean (%) | 1.95 | 1.87 | 2.08 | 1.58 | 1.95 |
| O3 mean | 0.0489*** | 0.0793*** | 0.0322*** | 0.0434*** | 0.0938*** |
| | (0.005) | (0.010) | (0.007) | (0.013) | (0.013) |
| Effect relative to mean (%) | 0.2 | 0.3 | 0.2 | 0.1 | 0.2 |
| Constant | 1.008 | 1.000 | -1.064 | 4.521* | -9.476*** |
| | (1.196) | (1.593) | (1.066) | (2.047) | (2.497) |
| Dependent variable mean | 25.30 | 30.91 | 13.67 | 43.41 | 45.78 |
| Observations | 8737915 | 8737907 | 8737920 | 8737867 | 8737863 |
| | 51 to 60 | Age 61 to 70 | Age 71 to 80 | Age 81 to 90 | Over 90 |
| NO2 mean | 1.050*** | 0.992*** | 0.722*** | 0.595*** | 0.128*** |
| | (0.087) | (0.071) | (0.065) | (0.057) | (0.021) |
| Effect relative to mean (%) | 1.32 | 1.67 | 1.50 | 0.96 | 0.91 |
| O3 mean | 0.123*** | 0.115*** | 0.101*** | 0.0495*** | 0.0108* |
| | (0.018) | (0.012) | (0.013) | (0.012) | (0.005) |
| Effect relative to mean (%) | 0.2 | 0.2 | 0.2 | 0.1 | 0.1 |
| Constant | 9.516** | -11.67*** | -10.41*** | 4.445 | 1.960* |
| | (3.109) | (2.519) | (2.290) | (2.507) | (0.880) |
| Dependent variable mean | 79.28 | 59.55 | 48.05 | 61.76 | 14.02 |
| Observations | 8737818 | 8737825 | 8737897 | 8737905 | 8737918 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include temperature and precipitation bins, day of the week, department by month, month by year and postcode fixed effects.

Table A16: Impact of pollution on health care expenditure by age, Wind IV model (entire sample)

| | Age 0 to 10 | Age 11 to 20 | Age 21 to 30 | Age 31 to 40 | Age 41 to 50 |
|---|---|---|---|---|---|
| NO2 mean | 0.384 | 1.124*** | -0.281 | 0.904* | 0.522 |
| | (0.207) | (0.280) | (0.184) | (0.397) | (0.319) |
| Effect relative to mean (%) | 1.52 | 3.64 | -2.06 | 2.08 | 1.14 |
| O3 mean | 0.184 | 0.532*** | -0.160 | 0.420* | 0.166 |
| | (0.095) | (0.132) | (0.086) | (0.193) | (0.148) |
| Effect relative to mean (%) | 0.7 | 1.7 | -1.2 | 1.0 | 0.4 |
| Dependent variable mean | 25.30 | 30.91 | 13.67 | 43.41 | 45.78 |
| Observations | 8484417 | 8484412 | 8484422 | 8484372 | 8484367 |
| First-stage F-stat | 8805.3 | 8806.1 | 8805.5 | 8804.8 | 8804.9 |

| | 51 to 60 | Age 61 to 70 | Age 71 to 80 | Age 81 to 90 | Over 90 |
|---|---|---|---|---|---|
| NO2 mean | 0.526 | 2.153*** | 1.322*** | 0.997** | -0.0519 |
| | (0.479) | (0.385) | (0.345) | (0.346) | (0.132) |
| Effect relative to mean (%) | 0.66 | 3.62 | 2.75 | 1.61 | -0.37 |
| O3 mean | 0.321 | 1.213*** | 0.765*** | 0.527** | -0.0138 |
| | (0.226) | (0.183) | (0.166) | (0.163) | (0.062) |
| Effect relative to mean (%) | 0.4 | 2.0 | 1.6 | 0.9 | -0.1 |
| Dependent variable mean | | | | | |
| Observations | 8484327 | 8484332 | 8484405 | 8484408 | 8484420 |
| First-stage F-stat | 8804.4 | 8805.0 | 8805.7 | 8805.6 | 8805.3 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include temperature and precipitation bins, day of the week, department by month, month by year and postcode fixed effects.

Table A17: Impact of pollution on health care expenditure by age, Strike IV model (entire sample)

| | Age 0 to 10 | Age 11 to 20 | Age 21 to 30 | Age 31 to 40 | Age 41 to 50 |
|---|---|---|---|---|---|
| NO2 mean | 1.578*** | 1.812*** | 0.410 | 2.179*** | 0.511 |
| | (0.250) | (0.380) | (0.292) | (0.574) | (0.464) |
| Effect relative to mean (%) | 6.24 | 5.86 | 3.00 | 5.02 | 1.12 |
| O3 mean | 1.402*** | 2.518*** | -1.017*** | 1.562** | -0.0514 |
| | (0.266) | (0.413) | (0.296) | (0.523) | (0.572) |
| Effect relative to mean (%) | 5.5 | 8.1 | -7.4 | 3.6 | -0.1 |
| Dependent variable mean | 25.30 | 30.91 | 13.67 | 43.41 | 45.78 |
| Observations | 6539947 | 6539945 | 6539950 | 6539912 | 6539903 |
| First-stage F-stat | 3765.9 | 3767.3 | 3765.7 | 3765.9 | 3765.5 |
| | 51 to 60 | Age 61 to 70 | Age 71 to 80 | Age 81 to 90 | Over 90 |
| NO2 mean | 3.733*** | 3.817*** | 3.277*** | 1.191* | -0.0935 |
| | (0.747) | (0.600) | (0.574) | (0.551) | (0.194) |
| Effect relative to mean (%) | 4.70 | 6.41 | 6.82 | 1.93 | -0.67 |
| O3 mean | 3.643*** | 1.539** | 2.543*** | 0.745 | 0.761** |
| | (0.763) | (0.585) | (0.531) | (0.521) | (0.233) |
| Effect relative to mean (%) | 4.6 | 2.6 | 5.3 | 1.2 | 5.4 |
| Dependent variable mean | 79.28 | 59.55 | 48.05 | 61.76 | 14.02 |
| Observations | 6539865 | 6539879 | 6539937 | 6539947 | 6539966 |
| First-stage F-stat | 3765.4 | 3765.8 | 3765.5 | 3765.3 | 3765.7 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include temperature and precipitation bins, day of the week, department by month, month by year and postcode fixed effects.

Table A18: OLS and IV estimates of effect of NO2 and O3 on health care expenditure

| | No chronic disease | | | Chronic disease | | |
|---|---|---|---|---|---|---|
| | OLS | Wind IV | Strike IV | OLS | Wind IV | Strike IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| NO2 mean | 3.461*** | 1.612** | 9.142*** | 4.296*** | 7.815*** | 7.249*** |
| | (0.239) | (0.604) | (1.005) | (0.332) | (0.919) | (1.487) |
| Effect relative to mean (%) | 1.61 | 0.75 | 4.25 | 1.79 | 3.25 | 3.02 |
| O3 mean | 0.392*** | 0.928** | 9.694*** | 0.481*** | 3.799*** | 1.382 |
| | (0.033) | (0.290) | (0.982) | (0.059) | (0.435) | (1.433) |
| Effect relative to mean (%) | 0.18 | 0.43 | 4.51 | 0.20 | 1.58 | 0.58 |
| Constant | 27.99*** | | | -155.5*** | | |
| | (6.157) | | | (16.724) | | |
| Dependent variable mean | 215.09 | 215.09 | 215.09 | 240.23 | 240.23 | 240.23 |
| Observations | 8472603 | 8484259 | 6539813 | 8472731 | 8484387 | 6539926 |
| First-stage F-stat | | 8805.3 | 3765.8 | | 8805.4 | 3765.4 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A19: OLS and IV estimates of effect of NO2 and O3 on health care expenditure

| | No CMU | | | CMU | | |
|---|---|---|---|---|---|---|
| | OLS | Wind IV | Strike IV | OLS | Wind IV | Strike IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| NO2 mean | 3.830*** | 4.097*** | 26.75*** | 0.359*** | 0.189 | 1.253*** |
| | (0.328) | (1.126) | (1.795) | (0.045) | (0.219) | (0.327) |
| Effect relative to mean (%) | 1.0 | 1.1 | 7.2 | 1.6 | 0.9 | 5.6 |
| O3 mean | 0.641*** | 1.830*** | 3.237* | 0.0538*** | 0.0966 | -0.0369 |
| | (0.053) | (0.548) | (1.591) | (0.010) | (0.104) | (0.339) |
| Effect relative to mean (%) | 0.2 | 0.5 | 0.9 | 0.2 | 0.4 | -0.2 |
| Constant | -295.7*** | | | -24.12*** | | |
| | (20.085) | | | (2.873) | | |
| Mean of dependent variable | 372.35 | 372.35 | 372.35 | 22.23 | 22.23 | 22.23 |
| Observations | 8495959 | 8484337 | 6539879 | 8496034 | 8484412 | 6539943 |
| First-stage F-stat | | 8804.9 | 3765.4 | | 8805.7 | 3765.6 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A20: OLS estimates of effect of NO2 and O3 on health care expenditure by medical specialty - entire sample

| | Family med. | O.R.L. | Ophtalmo. | Stoma. | Chir. den. |
|---|---|---|---|---|---|
| NO2 mean | 1.751*** | 0.0543*** | 0.198*** | 0.0232*** | 0.891*** |
| | (0.118) | (0.005) | (0.015) | (0.005) | (0.065) |
| O3 mean | 0.145*** | 0.00537*** | 0.0177*** | 0.00309** | 0.0818*** |
| | (0.019) | (0.001) | (0.003) | (0.001) | (0.010) |
| Constant | 58.46*** | -0.0172 | 2.391*** | 0.145 | 1.373 |
| | (3.967) | (0.154) | (0.406) | (0.177) | (1.718) |
| Observations | 8737859 | 8737946 | 8737944 | 8737950 | 8737935 |
| | Cardio-vasc. | Pneumology | Neurology | Gyneco. | Chir. trauma |
| NO2 mean | 0.140*** | 0.0339*** | 0.0393*** | 0.103*** | 0.0824*** |
| | (0.012) | (0.006) | (0.006) | (0.010) | (0.009) |
| O3 mean | 0.0113*** | 0.00261 | 0.00372* | 0.00726*** | 0.00792*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Constant | -0.239 | 0.957*** | 1.361*** | 1.124*** | -1.565*** |
| | (0.384) | (0.265) | (0.252) | (0.273) | (0.353) |
| Observations | 8737944 | 8737950 | 8737951 | 8737945 | 8737939 |
| | Ambulance | Gastro. hep. | Rhuma. | Nephrology | Chir. plas. |
| NO2 mean | 0.141*** | 0.0543*** | 0.0502*** | 0.0136*** | 0.0255*** |
| | (0.016) | (0.016) | (0.006) | (0.003) | (0.005) |
| O3 mean | 0.0267*** | 0.00636 | 0.00301 | 0.00247* | 0.00362** |
| | (0.004) | (0.005) | (0.002) | (0.001) | (0.001) |
| Constant | -3.908*** | -0.314 | 1.360*** | 0.509** | -0.493** |
| | (0.604) | (0.734) | (0.288) | (0.168) | (0.181) |
| Observations | 8737936 | 8737950 | 8737951 | 8737951 | 8737952 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.

Table A21: OLS estimates of effect of NO2 and O3 on health care expenditure by medical specialty - 10% most populated postcode areas

| | Family med. | O.R.L. | Ophtalmo. | Stoma. | Chir. den. |
|---|---|---|---|---|---|
| NO2 mean | 2.363*** | 0.0894*** | 0.274*** | 0.0518** | 1.526*** |
| | (0.306) | (0.014) | (0.044) | (0.019) | (0.188) |
| O3 mean | 0.248* | 0.00898 | 0.0316* | 0.00927 | 0.179** |
| | (0.117) | (0.007) | (0.015) | (0.006) | (0.054) |
| Constant | 243.0*** | -0.274 | 8.825** | 1.135 | 8.588 |
| | (28.920) | (1.034) | (2.788) | (1.481) | (12.240) |
| Observations | 874918 | 874923 | 874921 | 874925 | 874920 |

| | Cardio-vasc. | Pneumology | Neurology | Gyneco. | Chir. trauma |
|---|---|---|---|---|---|
| NO2 mean | 0.227*** | 0.0172 | 0.0705*** | 0.167*** | 0.117*** |
| | (0.039) | (0.018) | (0.019) | (0.032) | (0.030) |
| O3 mean | 0.0311* | 0.00143 | 0.00393 | 0.0261* | 0.00583 |
| | (0.013) | (0.011) | (0.008) | (0.012) | (0.013) |
| Constant | -0.0741 | 3.849* | 5.133*** | 5.840** | -6.222** |
| | (2.682) | (1.693) | (1.522) | (2.051) | (2.213) |
| Observations | 874919 | 874926 | 874926 | 874925 | 874924 |

| | Ambulance | Gastro. hep. | Rhuma. | Nephrology | Chir. plas. |
|---|---|---|---|---|---|
| NO2 mean | 0.268*** | 0.00417 | 0.0483* | 0.0192 | 0.0696*** |
| | (0.051) | (0.060) | (0.020) | (0.012) | (0.021) |
| O3 mean | 0.111*** | 0.0238 | 0.00331 | 0.0130 | 0.0182* |
| | (0.023) | (0.036) | (0.011) | (0.007) | (0.008) |
| Constant | -16.84*** | -7.958 | 4.594** | 1.663 | -2.076 |
| | (4.417) | (5.828) | (1.445) | (1.106) | (1.204) |
| Observations | 874919 | 874924 | 874926 | 874925 | 874926 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.

Table A22: OLS estimates of effect of NO2 and O3 on health care expenditure by medical specialty - sample of the biggest 70 cities

| | Family med. | O.R.L. | Ophtalmo. | Stoma. | Chir. den. |
|---|---|---|---|---|---|
| NO2 mean | 2.877*** | 0.111*** | 0.529*** | 0.0977* | 2.455*** |
| | (0.606) | (0.031) | (0.083) | (0.047) | (0.371) |
| O3 mean | 0.367 | 0.0169 | 0.0918* | 0.0136 | 0.336* |
| | (0.238) | (0.019) | (0.037) | (0.013) | (0.132) |
| Constant | 339.2*** | -0.261 | 11.47 | 5.471 | 0.801 |
| | (88.451) | (2.948) | (7.985) | (4.864) | (37.155) |
| Observations | 236760 | 236759 | 236757 | 236759 | 236759 |
| | Cardio-vasc. | Pneumology | Neurology | Gyneco. | Chir. trauma |
| NO2 mean | 0.265** | -0.0207 | 0.109** | 0.222** | 0.107 |
| | (0.085) | (0.040) | (0.040) | (0.073) | (0.066) |
| O3 mean | 0.0599 | 0.0272 | -0.00422 | 0.0381 | -0.0117 |
| | (0.033) | (0.026) | (0.018) | (0.033) | (0.026) |
| Constant | -2.941 | 5.193 | 10.69* | 10.93 | -6.028 |
| | (7.803) | (3.897) | (4.309) | (5.998) | (6.136) |
| Observations | 236753 | 236760 | 236760 | 236760 | 236758 |
| | Ambulance | Gastro. hep. | Rhuma. | Nephrology | Chir. plas. |
| NO2 mean | 0.401*** | 0.00657 | 0.0397 | 0.0217 | 0.110* |
| | (0.115) | (0.162) | (0.049) | (0.027) | (0.044) |
| O3 mean | 0.196*** | 0.171 | 0.0277 | 0.0389* | 0.0439* |
| | (0.058) | (0.114) | (0.029) | (0.019) | (0.022) |
| Constant | -30.26* | -23.81 | 6.016 | 0.845 | -5.607 |
| | (12.292) | (16.926) | (3.789) | (3.071) | (3.138) |
| Observations | 236758 | 236759 | 236760 | 236759 | 236760 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.

Table A23: Impact of pollution on health care expenditure by medical specialty, OLS model - sample of the 10% most populated postcode areas, interaction of weekday fixed effects with postcode fixed effects

| | Family medicine | O.R.L. | Ophthal-mology | Stomatology | Dentistry |
|---|---|---|---|---|---|
| NO2 mean | 2.552*** | 0.0551*** | 0.201*** | 0.0283 | 1.111*** |
| | (0.213) | (0.011) | (0.035) | (0.018) | (0.137) |
| O3 mean | 0.419*** | 0.0117 | 0.0179 | 0.00914 | 0.171** |
| | (0.115) | (0.006) | (0.015) | (0.006) | (0.054) |
| Observations | 835579 | 835585 | 835582 | 835586 | 835581 |

| | Cardio-vascular | Pneumology | Neurology | Gynecology | Ambulance |
|---|---|---|---|---|---|
| NO2 mean | 0.150*** | 0.0202 | 0.0899*** | 0.126*** | 0.312*** |
| | (0.033) | (0.019) | (0.019) | (0.026) | (0.049) |
| O3 mean | 0.0358** | 0.00587 | 0.00947 | 0.0153 | 0.110*** |
| | (0.012) | (0.012) | (0.009) | (0.012) | (0.022) |
| Observations | 835580 | 835587 | 835587 | 835586 | 835580 |

| | Gastro-hepatology | Rhuma-tology | Nephrology | Trauma surgery | Plastic surgery |
|---|---|---|---|---|---|
| NO2 mean | 0.0349 | 0.0488* | 0.00386 | 0.0842** | 0.0532* |
| | (0.068) | (0.020) | (0.014) | (0.028) | (0.022) |
| O3 mean | 0.0274 | -0.00210 | 0.0173* | 0.00169 | 0.0140 |
| | (0.030) | (0.010) | (0.007) | (0.014) | (0.008) |
| Observations | 835585 | 835587 | 835586 | 835585 | 835587 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week by postcode, month, year and postcode fixed effects.

Table A24: Impact of pollution on health care expenditure by medical specialty, OLS model - sample of the 70 biggest cities, interaction of weekday fixed effects with postcode fixed effects

| | Family medicine | O.R.L. | Ophthal-mology | Stomatology | Dentistry |
|---|---|---|---|---|---|
| NO2 mean | 3.330*** | 0.0729** | 0.422*** | 0.0562 | 2.010*** |
| | (0.480) | (0.027) | (0.076) | (0.044) | (0.302) |
| O3 mean | 0.498* | 0.0298 | 0.0438 | 0.0151 | 0.346* |
| | (0.205) | (0.017) | (0.040) | (0.015) | (0.139) |
| Observations | 214905 | 214905 | 214902 | 214904 | 214904 |
| | Cardio-vascular | Pneumology | Neurology | Gynecology | Ambulance |
| NO2 mean | 0.170* | -0.00336 | 0.127** | 0.191** | 0.489*** |
| | (0.080) | (0.042) | (0.045) | (0.067) | (0.117) |
| O3 mean | 0.0724* | 0.0329 | 0.00100 | 0.0172 | 0.186** |
| | (0.030) | (0.030) | (0.020) | (0.036) | (0.057) |
| Observations | 214898 | 214905 | 214905 | 214905 | 214903 |
| | Gastro-hepatology | Rhuma-tology | Nephrology | Trauma surgery | Plastic surgery |
| NO2 mean | 0.0783 | 0.0595 | -0.000550 | 0.0530 | 0.0961 |
| | (0.193) | (0.049) | (0.033) | (0.067) | (0.050) |
| O3 mean | 0.138 | 0.0247 | 0.0434* | -0.0180 | 0.0412 |
| | (0.099) | (0.027) | (0.020) | (0.032) | (0.023) |
| Observations | 214904 | 214905 | 214904 | 214903 | 214905 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week by postcode, month, year and postcode fixed effects.

Table A25: Strike IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - entire sample

| | General med. | O.R.L. | Ophtalmo. | Stoma. | Chir. den. |
|---|---|---|---|---|---|
| NO2 mean | 5.883*** | 0.108* | 0.466*** | 0.0820 | 3.642*** |
| | (0.702) | (0.044) | (0.118) | (0.045) | (0.496) |
| O3 mean | 4.119*** | 0.146** | 0.798*** | 0.0141 | 2.412*** |
| | (0.773) | (0.048) | (0.132) | (0.052) | (0.509) |
| Observations | 6539891 | 6539971 | 6539968 | 6539973 | 6539966 |
| First-stage F-stat | 3765.9 | 3765.8 | 3765.6 | 3765.8 | 3765.9 |

| | Cardio-vasc. | Pneumology | Neurology | Gyneco. | Ambulance |
|---|---|---|---|---|---|
| NO2 mean | 0.283** | 0.0453 | 0.111 | 0.351*** | 0.338* |
| | (0.096) | (0.090) | (0.082) | (0.087) | (0.161) |
| O3 mean | 0.382*** | 0.314*** | 0.368*** | 0.317*** | 0.339* |
| | (0.106) | (0.095) | (0.111) | (0.076) | (0.157) |
| Observations | 6539973 | 6539972 | 6539974 | 6539970 | 6539963 |
| First-stage F-stat | 3765.8 | 3765.8 | 3765.8 | 3766.9 | 3765.8 |

| | Gastro. hep. | Rhuma. | Nephrology | Chir. trauma | Chir. plas. |
|---|---|---|---|---|---|
| NO2 mean | 0.429 | 0.0984 | 0.0169 | 0.412*** | 0.179* |
| | (0.232) | (0.094) | (0.043) | (0.117) | (0.070) |
| O3 mean | 0.259 | 0.253** | 0.0143 | 0.380** | -0.0108 |
| | (0.295) | (0.096) | (0.049) | (0.122) | (0.054) |
| Observations | 6539972 | 6539973 | 6539973 | 6539962 | 6539974 |
| First-stage F-stat | 3765.8 | 3765.8 | 3765.8 | 3765.6 | 3765.8 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.

Table A26: Strike IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - 10% most populated postcode areas

| | General med. | O.R.L. | Ophtalmo. | Stoma. | Chir. den. |
|---|---|---|---|---|---|
| NO2 mean | 17.25 | 1.094* | 1.428 | 0.0979 | 22.26*** |
| | (10.595) | (0.524) | (1.441) | (0.715) | (6.246) |
| O3 mean | 12.01 | 0.759* | 0.814 | -0.0128 | 12.41*** |
| | (7.142) | (0.330) | (0.925) | (0.442) | (3.715) |
| Observations | 637449 | 637453 | 637451 | 637453 | 637453 |
| First-stage F-stat | 425.0 | 424.8 | 424.8 | 424.8 | 424.8 |
| | **Cardio-vasc.** | **Pneumology** | **Neurology** | **Gyneco.** | **Ambulance** |
| NO2 mean | 1.194 | 1.438 | 0.964 | 4.444*** | -2.607 |
| | (1.113) | (1.177) | (0.843) | (1.280) | (2.046) |
| O3 mean | 1.224 | 1.203 | 0.503 | 1.918* | 4.087** |
| | (0.819) | (0.701) | (0.579) | (0.750) | (1.473) |
| Observations | 637454 | 637454 | 637454 | 637454 | 637449 |
| First-stage F-stat | 424.8 | 424.8 | 424.8 | 424.8 | 424.8 |
| | **Gastro. hep.** | **Rhuma.** | **Nephrology** | **Chir. trauma** | **Chir. plas.** |
| NO2 mean | 3.665 | 0.847 | -0.882 | 3.165* | 1.384 |
| | (3.995) | (0.968) | (0.691) | (1.473) | (1.042) |
| O3 mean | 0.212 | 0.742 | -0.626 | 0.605 | 0.660 |
| | (2.585) | (0.581) | (0.479) | (0.940) | (0.592) |
| Observations | 637452 | 637454 | 637453 | 637452 | 637454 |
| First-stage F-stat | 424.8 | 424.8 | 424.8 | 424.8 | 424.8 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.

Table A27: Strike IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - 10% most populated postcode areas - sample of the biggest 70 cities

| | General med. | O.R.L. | Ophtalmo. | Stoma. | Chir. den. |
|---|---|---|---|---|---|
| NO2 mean | 26.66 | 2.548 | 2.940 | -1.683 | 49.18** |
| | (22.030) | (1.324) | (3.301) | (1.738) | (15.064) |
| O3 mean | 16.48 | 1.383 | 2.351 | -1.018 | 25.47** |
| | (15.834) | (0.889) | (2.024) | (1.166) | (8.949) |
| Observations | 162491 | 162491 | 162490 | 162490 | 162491 |
| First-stage F-stat | 162.3 | 162.3 | 162.3 | 162.3 | 162.3 |
| | Cardio-vasc. | Pneumology | Neurology | Gyneco. | Ambulance |
| NO2 mean | 0.430 | 3.011 | -0.242 | 5.438* | -6.408 |
| | (2.442) | (2.251) | (2.015) | (2.615) | (4.429) |
| O3 mean | 1.166 | 2.429 | -0.217 | 1.515 | 4.148 |
| | (1.463) | (1.377) | (1.441) | (1.532) | (3.164) |
| Observations | 162491 | 162491 | 162491 | 162491 | 162489 |
| First-stage F-stat | 162.3 | 162.3 | 162.3 | 162.3 | 162.3 |
| | Gastro. hep. | Rhuma. | Nephrology | Chir. trauma | Chir. plas. |
| NO2 mean | 10.17 | 2.857 | -0.439 | 3.905 | 1.376 |
| | (9.961) | (2.496) | (1.591) | (3.287) | (2.000) |
| O3 mean | 2.460 | 2.220 | -0.662 | 0.810 | 0.0277 |
| | (6.360) | (1.491) | (1.073) | (2.290) | (1.157) |
| Observations | 162490 | 162491 | 162490 | 162489 | 162491 |
| First-stage F-stat | 162.3 | 162.3 | 162.3 | 162.3 | 162.3 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.

Table A28: Impact of pollution on health care expenditure by medical specialty, strike IV model - sample of the 10% most populated postcode areas, interaction of weekday fixed effects with postcode fixed effects

| | Family medicine | O.R.L. | Ophthal-mology | Stomatology | Dentistry |
|---|---|---|---|---|---|
| NO2 mean | 16.83*** | 0.184 | 1.263** | 0.101 | 6.412** |
| | (2.828) | (0.179) | (0.478) | (0.218) | (2.061) |
| O3 mean | 8.354* | 0.489 | 2.140** | -0.0466 | 8.454*** |
| | (4.001) | (0.250) | (0.658) | (0.292) | (2.557) |
| Observations | 637449 | 637453 | 637451 | 637453 | 637453 |
| First-stage F-stat | 492.0 | 491.8 | 491.8 | 491.8 | 491.8 |
| | Cardio-vascular | Pneumology | Neurology | Gynecology | Ambulance |
| NO2 mean | 0.0686 | 0.296 | 0.568* | 1.399*** | -0.480 |
| | (0.379) | (0.412) | (0.283) | (0.374) | (0.680) |
| O3 mean | 0.870 | 1.016* | 1.033* | 0.705 | 0.365 |
| | (0.593) | (0.435) | (0.406) | (0.411) | (0.834) |
| Observations | 637454 | 637454 | 637454 | 637454 | 637449 |
| First-stage F-stat | 491.8 | 491.8 | 491.8 | 491.8 | 491.8 |
| | Gastro-hepatology | Rhuma-tology | Nephrology | Trauma surgery | Plastic surgery |
| NO2 mean | 2.851* | 0.340 | 0.0653 | 1.756*** | 0.450 |
| | (1.153) | (0.299) | (0.207) | (0.479) | (0.305) |
| O3 mean | 0.325 | 0.966* | -0.0351 | 0.899 | 0.0786 |
| | (1.582) | (0.408) | (0.269) | (0.615) | (0.286) |
| Observations | 637452 | 637454 | 637453 | 637452 | 637454 |
| First-stage F-stat | 491.8 | 491.8 | 491.8 | 491.8 | 491.8 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week by postcode, month, year and postcode fixed effects.

Table A29: Impact of pollution on health care expenditure by medical specialty, strike IV model - sample of the 70 biggest cities, interaction of weekday fixed effects with postcode fixed effects

| | Family medicine | O.R.L. | Ophthal-mology | Stomatology | Dentistry |
|---|---|---|---|---|---|
| NO2 mean | 31.94* | 1.371 | 3.303 | -1.513 | 34.59** |
| | (14.790) | (0.973) | (2.401) | (1.349) | (10.886) |
| O3 mean | 21.44 | 0.907 | 3.232 | -1.007 | 20.48** |
| | (12.236) | (0.795) | (1.784) | (1.038) | (7.560) |
| Observations | 162491 | 162491 | 162490 | 162490 | 162491 |
| First-stage F-stat | 217.7 | 217.7 | 217.7 | 217.7 | 217.7 |
| | Cardio-vascular | Pneumology | Neurology | Gynecology | Ambulance |
| NO2 mean | 0.00835 | 3.079 | 0.251 | 3.912* | -4.865 |
| | (1.759) | (1.682) | (1.517) | (1.844) | (3.214) |
| O3 mean | 1.028 | 2.704* | 0.122 | 1.122 | 4.685 |
| | (1.298) | (1.280) | (1.294) | (1.248) | (2.847) |
| Observations | 162491 | 162491 | 162491 | 162491 | 162489 |
| First-stage F-stat | 217.7 | 217.7 | 217.7 | 217.7 | 217.7 |
| | Gastro-hepatology | Rhuma-tology | Nephrology | Trauma surgery | Plastic surgery |
| NO2 mean | 7.933 | 2.869 | -0.545 | 2.958 | 0.684 |
| | (7.101) | (1.791) | (1.172) | (2.389) | (1.343) |
| O3 mean | 2.195 | 2.481* | -0.740 | 0.662 | -0.299 |
| | (5.373) | (1.260) | (0.925) | (1.965) | (0.948) |
| Observations | 162490 | 162491 | 162490 | 162489 | 162491 |
| First-stage F-stat | 217.7 | 217.7 | 217.7 | 217.7 | 217.7 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week by postcode, month, year and postcode fixed effects.

Table A30: Wind IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - entire sample

| | General med. | O.R.L. | Ophtalmo. | Stoma. | Chir. den. |
|---|---|---|---|---|---|
| NO2 mean | 1.777*** | -0.0338 | 0.0187 | 0.00894 | 0.0615 |
| | (0.466) | (0.028) | (0.077) | (0.031) | (0.273) |
| O3 mean | 0.959*** | -0.0145 | 0.0142 | 0.00501 | 0.0182 |
| | (0.217) | (0.013) | (0.036) | (0.014) | (0.127) |
| Observations | 8484366 | 8484449 | 8484446 | 8484452 | 8484437 |
| First-stage F-stat | 8805.1 | 8805.3 | 8805.4 | 8805.3 | 8805.3 |
| | Cardio-vasc. | Pneumology | Neurology | Gyneco. | Ambulance |
| NO2 mean | -0.0379 | -0.0597 | 0.00361 | 0.0371 | 0.838*** |
| | (0.056) | (0.072) | (0.059) | (0.048) | (0.111) |
| O3 mean | -0.0149 | -0.0286 | 0.00362 | 0.0198 | 0.413*** |
| | (0.027) | (0.033) | (0.027) | (0.023) | (0.052) |
| Observations | 8484446 | 8484452 | 8484453 | 8484448 | 8484439 |
| First-stage F-stat | 8805.2 | 8805.3 | 8805.3 | 8805.4 | 8805.3 |
| | Gastro. hep. | Rhuma. | Nephrology | Chir. trauma | Chir. plas. |
| NO2 mean | 0.250 | 0.0484 | 0.0293 | 0.0551 | -0.00423 |
| | (0.178) | (0.066) | (0.031) | (0.071) | (0.036) |
| O3 mean | 0.110 | 0.0234 | 0.0141 | 0.0295 | -0.00533 |
| | (0.084) | (0.030) | (0.014) | (0.034) | (0.017) |
| Observations | 8484452 | 8484453 | 8484453 | 8484441 | 8484454 |
| First-stage F-stat | 8805.3 | 8805.3 | 8805.3 | 8805.3 | 8805.3 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.

Table A31: Wind IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - 10% most populated postcode areas

| | General med. | O.R.L. | Ophtalmo. | Stoma. | Chir. den. |
|---|---|---|---|---|---|
| NO2 mean | 4.275** | -0.0571 | 0.0564 | -0.00259 | 0.0470 |
| | (1.307) | (0.087) | (0.213) | (0.097) | (0.786) |
| O3 mean | 3.578*** | -0.0327 | 0.0661 | 0.0102 | -0.0568 |
| | (0.864) | (0.057) | (0.140) | (0.064) | (0.508) |
| Observations | 836729 | 836735 | 836732 | 836736 | 836731 |
| First-stage F-stat | 1355.9 | 1355.9 | 1356.0 | 1355.9 | 1355.9 |
| | Cardio-vasc. | Pneumology | Neurology | Gyneco. | Ambulance |
| NO2 mean | 0.151 | -0.200 | 0.322* | 0.170 | 2.443*** |
| | (0.166) | (0.227) | (0.147) | (0.143) | (0.366) |
| O3 mean | 0.109 | -0.108 | 0.212* | 0.148 | 1.639*** |
| | (0.113) | (0.144) | (0.095) | (0.098) | (0.239) |
| Observations | 836730 | 836737 | 836737 | 836736 | 836730 |
| First-stage F-stat | 1355.8 | 1355.9 | 1355.9 | 1355.9 | 1355.9 |
| | Gastro. hep. | Rhuma. | Nephrology | Chir. trauma | Chir. plas. |
| NO2 mean | 0.640 | -0.0824 | 0.104 | 0.118 | -0.0750 |
| | (0.609) | (0.135) | (0.084) | (0.191) | (0.111) |
| O3 mean | 0.368 | -0.0316 | 0.0765 | 0.0737 | -0.0841 |
| | (0.396) | (0.088) | (0.054) | (0.130) | (0.075) |
| Observations | 836735 | 836737 | 836736 | 836735 | 836737 |
| First-stage F-stat | 1355.9 | 1355.9 | 1355.9 | 1355.9 | 1355.9 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.

Table A32: Wind IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - 10% most populated postcode areas - sample of the biggest 70 cities

| | General med. | O.R.L. | Ophtalmo. | Stoma. | Chir. den. |
|---|---|---|---|---|---|
| NO2 mean | 3.905 | -0.213 | -0.101 | 0.139 | -0.272 |
| | (2.634) | (0.203) | (0.489) | (0.242) | (1.734) |
| O3 mean | 3.794 | -0.122 | -0.139 | 0.137 | -0.585 |
| | (2.021) | (0.159) | (0.381) | (0.187) | (1.328) |
| Observations | 215203 | 215203 | 215200 | 215202 | 215202 |
| First-stage F-stat | 551.1 | 551.1 | 551.0 | 551.0 | 551.1 |

| | Cardio-vasc. | Pneumology | Neurology | Gyneco. | Ambulance |
|---|---|---|---|---|---|
| NO2 mean | 0.0397 | -0.520 | 0.997** | 0.730* | 3.747*** |
| | (0.370) | (0.511) | (0.351) | (0.318) | (0.878) |
| O3 mean | 0.0367 | -0.389 | 0.743** | 0.612* | 2.948*** |
| | (0.301) | (0.406) | (0.265) | (0.263) | (0.649) |
| Observations | 215196 | 215203 | 215203 | 215203 | 215201 |
| First-stage F-stat | 551.0 | 551.1 | 551.1 | 551.1 | 551.2 |

| | Gastro. hep. | Rhuma. | Nephrology | Chir. trauma | Chir. plas. |
|---|---|---|---|---|---|
| NO2 mean | 0.927 | -0.588* | 0.100 | -0.182 | -0.328 |
| | (1.482) | (0.298) | (0.189) | (0.424) | (0.238) |
| O3 mean | 0.613 | -0.379 | 0.108 | -0.108 | -0.262 |
| | (1.177) | (0.223) | (0.140) | (0.361) | (0.190) |
| Observations | 215202 | 215203 | 215202 | 215201 | 215203 |
| First-stage F-stat | 551.1 | 551.1 | 551.1 | 551.1 | 551.1 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.

Table A33: Impact of pollution on health care expenditure by medical specialty, wind IV model - sample of the 10% most populated postcode areas, interaction of weekday fixed effects with postcode fixed effects

| | Family medicine | O.R.L. | Ophthal-mology | Stomatology | Dentistry |
|---|---|---|---|---|---|
| NO2 mean | 6.177* | 0.147 | 0.319 | 0.250 | 2.742 |
| | (2.699) | (0.153) | (0.441) | (0.211) | (1.540) |
| O3 mean | 7.267** | 0.179 | 0.382 | 0.270 | 3.080* |
| | (2.477) | (0.139) | (0.400) | (0.193) | (1.387) |
| Observations | 836729 | 836735 | 836732 | 836736 | 836731 |
| First-stage F-stat | 1243.1 | 1243.1 | 1243.1 | 1243.1 | 1243.0 |

| | Cardio-vascular | Pneumology | Neurology | Gynecology | Ambulance |
|---|---|---|---|---|---|
| NO2 mean | 0.395 | -0.459 | 0.488 | 0.418 | 3.647*** |
| | (0.346) | (0.500) | (0.311) | (0.312) | (0.706) |
| O3 mean | 0.458 | -0.413 | 0.405 | 0.465 | 3.378*** |
| | (0.321) | (0.444) | (0.279) | (0.285) | (0.652) |
| Observations | 836730 | 836737 | 836737 | 836736 | 836730 |
| First-stage F-stat | 1243.0 | 1243.1 | 1243.1 | 1243.1 | 1243.1 |

| | Gastro-hepatology | Rhuma-tology | Nephrology | Trauma surgery | Plastic surgery |
|---|---|---|---|---|---|
| NO2 mean | 1.094 | -0.0973 | -0.111 | 0.520 | -0.357 |
| | (1.299) | (0.292) | (0.164) | (0.414) | (0.246) |
| O3 mean | 0.941 | -0.0504 | -0.102 | 0.526 | -0.361 |
| | (1.172) | (0.263) | (0.148) | (0.382) | (0.228) |
| Observations | 836735 | 836737 | 836736 | 836735 | 836737 |
| First-stage F-stat | 1243.1 | 1243.1 | 1243.2 | 1243.1 | 1243.1 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week by postcode, month, year and postcode fixed effects.

Table A34: Impact of pollution on health care expenditure by medical specialty, wind IV model - sample of the 70 biggest cities, interaction of weekday fixed effects with postcode fixed effects

| | Family medicine | O.R.L. | Ophthal-mology | Stomatology | Dentistry |
|---|---|---|---|---|---|
| NO2 mean | 1.746 | -0.212 | -0.176 | 0.146 | -0.276 |
| | (2.366) | (0.195) | (0.475) | (0.243) | (1.684) |
| O3 mean | 2.270 | -0.104 | -0.153 | 0.148 | -0.433 |
| | (1.818) | (0.152) | (0.371) | (0.189) | (1.285) |
| Observations | 215203 | 215203 | 215200 | 215202 | 215202 |
| First-stage F-stat | 546.6 | 546.6 | 546.5 | 546.5 | 546.6 |

| | Cardio-vascular | Pneumology | Neurology | Gynecology | Ambulance |
|---|---|---|---|---|---|
| NO2 mean | 0.0848 | -0.564 | 0.919** | 0.644* | 3.708*** |
| | (0.354) | (0.514) | (0.347) | (0.298) | (0.873) |
| O3 mean | 0.0998 | -0.428 | 0.688** | 0.559* | 2.976*** |
| | (0.288) | (0.412) | (0.263) | (0.246) | (0.655) |
| Observations | 215196 | 215203 | 215203 | 215203 | 215201 |
| First-stage F-stat | 546.5 | 546.6 | 546.6 | 546.6 | 546.6 |

| | Gastro-hepatology | Rhuma-tology | Nephrology | Trauma surgery | Plastic surgery |
|---|---|---|---|---|---|
| NO2 mean | 0.860 | -0.612* | 0.0910 | -0.175 | -0.322 |
| | (1.422) | (0.292) | (0.185) | (0.421) | (0.239) |
| O3 mean | 0.568 | -0.394 | 0.108 | -0.0876 | -0.256 |
| | (1.139) | (0.218) | (0.137) | (0.358) | (0.190) |
| Observations | 215202 | 215203 | 215202 | 215201 | 215203 |
| First-stage F-stat | 546.6 | 546.6 | 546.6 | 546.5 | 546.6 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week by postcode, month, year and postcode fixed effects.

Table A35: OLS and IV estimates of effect of NO2 and O3 on health care expenditure - simpler fixed effect structure

| | Total spending - entire France | | | Total spending - 70 biggest cities | | |
|---|---|---|---|---|---|---|
| | OLS | Wind IV | Strike IV | OLS | Wind IV | Strike IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| NO2 mean | 5.784*** | 7.566*** | 21.68*** | 16.52*** | 24.74* | 113.6*** |
| | (0.380) | (1.240) | (2.061) | (2.588) | (9.964) | (22.742) |
| O3 mean | 0.894*** | 3.942*** | 19.68*** | 5.798*** | 23.51** | 76.79** |
| | (0.059) | (0.591) | (1.947) | (0.847) | (8.007) | (26.583) |
| Constant | 71.34*** | | | 659.3* | | |
| | (16.501) | | | (312.327) | | |
| Observations | 8495951 | 8484329 | 6539870 | 215497 | 215203 | 162491 |
| First-stage F-stat | | 8805.0 | 3765.3 | | 575.4 | 171.4 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month, year, and postcode fixed effects.

Table A36: OLS and IV estimates of effect of NO2 and O3 on health care expenditure - simpler time fixed effect structure, excluding also day of week fixed effecst

| | Total spending - entire France | | | Total spending - 70 biggest cities | | |
|---|---|---|---|---|---|---|
| | OLS | Wind IV | Strike IV | OLS | Wind IV | Strike IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| NO2 mean | 17.35*** | 24.82*** | 30.96*** | 69.19*** | 73.06*** | 294.5*** |
| | (0.586) | (1.296) | (3.179) | (6.609) | (11.286) | (35.406) |
| O3 mean | 1.800*** | 12.25*** | 123.7*** | 9.684*** | 61.16*** | 486.8*** |
| | (0.073) | (0.631) | (5.622) | (1.154) | (9.190) | (67.012) |
| Constant | 85.52*** | | | 856.4** | | |
| | (15.125) | | | (288.059) | | |
| Observations | 8495951 | 8484329 | 6539870 | 215497 | 215203 | 162491 |
| First-stage F-stat | | 8259.5 | 3665.6 | | 581.4 | 252.9 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and, month, year, and postcode fixed effects.

Table A37: OLS and IV estimates of effect of NO2 and O3 on health care expenditure - no weather controls

| | Total spending - entire France | | | Total spending - 70 biggest cities | | |
|---|---|---|---|---|---|---|
| | OLS | Wind IV | Strike IV | OLS | Wind IV | Strike IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| NO2 mean | 4.172*** | 11.92*** | 14.76*** | 10.90*** | 36.35** | 143.7** |
| | (0.300) | (2.058) | (2.655) | (1.893) | (13.423) | (54.796) |
| O3 mean | 0.438*** | 7.710*** | 20.22*** | 2.925*** | 36.71** | 124.7** |
| | (0.039) | (1.246) | (1.899) | (0.552) | (12.452) | (38.515) |
| Constant | -2.612 | | | 123.5 | | |
| | (16.075) | | | (315.979) | | |
| Observations | 8761843 | 8484329 | 6743844 | 237412 | 215203 | 178993 |
| First-stage F-stat | | 9163.6 | 2665.8 | | 654.1 | 90.17 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include month by department, month by year, and postcode fixed effects.

Table A38: OLS and IV estimates of effect of NO2 and O3 on health care expenditure - no weather controls and simple fixed effect structure

| | Total spending - entire France | | | Total spending - 70 biggest cities | | |
|---|---|---|---|---|---|---|
| | OLS | Wind IV | Strike IV | OLS | Wind IV | Strike IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| NO2 mean | 4.185*** | 11.92*** | 14.76*** | 12.17*** | 39.09* | 133.8*** |
| | (0.286) | (2.058) | (2.655) | (1.988) | (15.892) | (25.661) |
| O3 mean | 0.494*** | 7.710*** | 20.22*** | 3.478*** | 41.47** | 85.04** |
| | (0.038) | (1.246) | (1.899) | (0.589) | (15.233) | (26.226) |
| Constant | 128.4*** | | | 1026.7*** | | |
| | (13.017) | | | (235.598) | | |
| Observations | 8761843 | 8484329 | 6743844 | 237412 | 215203 | 178993 |
| First-stage F-stat | | 9163.6 | 2665.8 | | 678.1 | 148.0 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include month, year, and postcode fixed effects.

Table A39: OLS and IV estimates of effect NO2 and O3 on health care expenditure, inclusion of pollution and weather lags

| | Total spending - entire France | | | Total spending - 70 biggest cities | | |
|---|---|---|---|---|---|---|
| | OLS (1) | Wind IV (2) | Strike IV (3) | OLS (4) | Wind IV (5) | Strike IV (6) |
| NO2 mean | 7.230*** | 29.81*** | 40.73*** | 16.17*** | 66.31** | 120.8* |
| | (0.498) | (2.745) | (4.115) | (2.756) | (21.956) | (51.479) |
| O3 mean | 0.866*** | 15.76*** | 15.19*** | 4.840*** | 60.83** | 167.3** |
| | (0.072) | (1.464) | (3.620) | (0.839) | (19.753) | (52.772) |
| Constant | 24.30 | | | -27.59 | | |
| | (15.364) | | | (400.410) | | |
| Observations | 8472673 | 8472673 | 6518056 | 214905 | 214905 | 161943 |
| First-stage F-stat | | 7364.7 | 1768.0 | | 576.7 | 111.2 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A40: IV estimates of effect of NO2 and O3 on health care expenditure, different strike IV specifications

| | Total spent[a] | Total spent[b] | Total spent[c] | Total spent[d] | Total spent[e] |
|---|---|---|---|---|---|
| NO2 mean | 38.79*** | 19.42*** | | | 20.09*** |
| | (3.296) | (2.022) | | | (2.312) |
| O3 mean | | | 39.29*** | 17.27*** | 22.31*** |
| | | | (3.757) | (1.944) | (2.492) |
| PM 10 mean | | | | | 6.000 |
| | | | | | (3.697) |
| Observations | 6539870 | 6539870 | 6539870 | 6539870 | 6539870 |
| First-stage F-stat | 2756.9 | 3765.3 | 484.3 | 1515.7 | 3765.3 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

[a] - NO2 pollution instrumented by a dummy equal to 1 when a strike takes place the first, second or third day, and 0 otherwise.

[b] - NO2 pollution instrumented by three dummies equal to 1 when a strike takes place the first day, second or third day, respectively and 0 otherwise.

[c] - O3 pollution instrumented by a dummy equal to 1 when a strike takes place the first, second or third day, and 0 otherwise.

[d] - O3 pollution instrumented by three dummies equal to 1 when a strike takes place the first day, second or third day, respectively and 0 otherwise.

[e] - NO2, O3 and PM pollution simultaneously instrumented by three dummies equal to 1 when a strike takes place the first day, second or third day, respectively and 0 otherwise.

Table A41: IV estimates of effect of NO2 and O3 on health care expenditure, different wind IV specifications

| | Total spent[a] | Total spent[b] | Total spent[c] | Total spent[d] |
|---|---|---|---|---|
| NO2 mean | -0.348 | -0.794*** | | |
| | (0.192) | (0.190) | | |
| O3 mean | | | 0.173 | 0.436*** |
| | | | (0.096) | (0.090) |
| Observations | 8495951 | 8484329 | 8495951 | 8484329 |
| First-stage F-stat | 21289.0 | 8805.0 | 73950.1 | 27595.0 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

[a] - NO2 pollution instrumented by a dummy equal to 1 when wind is below average on day t.

[b] - NO2 pollution instrumented by three dummies equal to 1 when wind is below average on day t, t-1, and t-2 respectively and 0 otherwise.

[c] - O3 pollution instrumented by a dummy equal to 1 when wind is below average on day t.

[d] - O3 pollution instrumented by three dummies equal to 1 when wind is below average on day t, t-1, and t-2 respectively and 0 otherwise.

Table A42: OLS and IV estimates of effect NO2 and O3 on health care expenditure - controlling for PM10 and PM2.5

| | Total spending - PM10 control | | | Total spending - PM2.5 control | | |
|---|---|---|---|---|---|---|
| | OLS | Wind IV | Strike IV | OLS | Wind IV | Strike IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| NO2 mean | 6.542*** | 7.409*** | 20.72*** | 6.725*** | 7.589*** | 21.32*** |
| | (0.455) | (0.941) | (2.277) | (0.460) | (1.056) | (2.013) |
| O3 mean | 0.799*** | 3.735*** | 21.00*** | 0.688*** | 3.845*** | 22.35*** |
| | (0.057) | (0.394) | (2.346) | (0.051) | (0.459) | (2.469) |
| PM 10 mean | -1.298*** | -0.363 | 1.907 | | | |
| | (0.124) | (0.218) | (1.511) | | | |
| PM 2.5 mean | | | | -2.071*** | -0.307 | 6.059** |
| | | | | (0.165) | (0.202) | (1.964) |
| Constant | -47.40* | | | -45.73* | | |
| | (18.741) | | | (18.691) | | |
| Observations | 8495951 | 8484329 | 6539870 | 8490140 | 8478518 | 6534790 |
| First-stage F-stat | | 9716.0 | 3824.1 | | 7321.4 | 5085.0 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A43: IV estimates of effect PM10 or PM2.5 and O3 on health care expenditure, controlling for NO2

| | Tot. spending - PM10 and O3 | | Tot. spending - PM2.5 and O3 | |
|---|---|---|---|---|
| | Wind IV | Strike IV | Wind IV | Strike IV |
| | (1) | (2) | (3) | (4) |
| PM 10 mean | 1.226* | 5.790 | | |
| | (0.609) | (3.680) | | |
| PM 2.5 mean | | | 1.495 | 7.729* |
| | | | (0.837) | (3.620) |
| O3 mean | 5.783*** | 19.23*** | 5.880*** | 20.54*** |
| | (0.396) | (2.028) | (0.427) | (2.219) |
| NO2 mean | 10.59*** | 22.77*** | 10.64*** | 23.58*** |
| | (0.680) | (1.917) | (0.686) | (1.655) |
| Constant | 151.2 | | | |
| | (351.979) | | | |
| Observations | 8484329 | 6539870 | 162491 | 6534790 |
| First-stage F-stat | 12978.7 | 2717.5 | 20.78 | 3768.2 |

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month, year, and postcode fixed effects.

Table A44: OLS and IV estimates of effect of log NO2 and log O3 on log health care expenditure

| | Total spending - entire France, OLS regressions | | | |
|---|---|---|---|---|
| NO2 mean | 4.677*** | | | |
| | (0.326) | | | |
| O3 mean | | -0.248*** | | |
| | | (0.034) | | |
| PM 10 mean | | | 0.875*** | |
| | | | (0.080) | |
| PM 2.5 mean | | | | 0.408*** |
| | | | | (0.069) |
| Constant | 14.66 | 84.97*** | 52.30*** | 63.09*** |
| | (15.167) | (11.561) | (13.099) | (12.595) |
| Observations | 8495951 | 8495951 | 8495951 | 8490140 |

| | Total spending - entire France, Wind IV regressions | | | |
|---|---|---|---|---|
| NO2 mean | -0.794*** | | | |
| | (0.190) | | | |
| O3 mean | | 0.436*** | | |
| | | (0.090) | | |
| PM 10 mean | | | -1.487*** | |
| | | | (0.244) | |
| PM 2.5 mean | | | | -1.509*** |
| | | | | (0.259) |
| Observations | 8484329 | 8484329 | 8484329 | 8478518 |
| First-stage F-stat | 8805.0 | 27595.0 | 6953.4 | 9292.5 |

| | Total spending - entire France, Strike IV regressions | | | |
|---|---|---|---|---|
| NO2 mean | 19.42*** | | | |
| | (2.022) | | | |
| O3 mean | | 17.27*** | | |
| | | (1.944) | | |
| PM 10 mean | | | -2.832 | |
| | | | (2.629) | |
| PM 2.5 mean | | | | -15.97*** |
| | | | | (2.837) |
| Observations | 6539870 | 6539870 | 6539870 | 6534790 |
| First-stage F-stat | 3765.3 | 1515.7 | 3126.4 | 3220.1 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month, year, and postcode fixed effects.

Table A45: OLS and IV estimates of effect of NO2 and O3 on health insurance reimbursements for sick leave

| | Sick leave spending - entire France | | | Sick leave spending - 70 biggest cities | | |
|---|---|---|---|---|---|---|
| | OLS | Wind IV | Strike IV | OLS | Wind IV | Strike IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| NO2 mean | 0.00835* | 0.147* | 0.118 | -0.0264 | -0.267 | -2.190 |
| | (0.004) | (0.065) | (0.105) | (0.033) | (0.220) | (1.635) |
| O3 mean | 0.00530** | 0.0761* | -0.412*** | -0.00279 | -0.152 | -1.268 |
| | (0.002) | (0.031) | (0.089) | (0.014) | (0.173) | (1.000) |
| Constant | 1.205*** | | | 6.032* | | |
| | (0.251) | | | (2.608) | | |
| Observations | 8496076 | 8484454 | 6539974 | 215497 | 215203 | 162491 |
| First-stage F-stat | | 8805.3 | 3765.8 | | 551.1 | 162.3 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A46: OLS and IV estimates of effect of NO2 and O3 on number of deaths

| | Number of deaths - entire France | | | Number of deaths - 70 biggest cities | | |
|---|---|---|---|---|---|---|
| | OLS | Wind IV | Strike IV | OLS | Wind IV | Strike IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| NO2 mean | 0.0000130** | -0.0000819 | -0.000157 | 0.0000626 | -0.000375 | 0.00136 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.002) |
| O3 mean | 0.00000327* | -0.0000419 | -0.000209* | 0.0000103 | -0.000286 | 0.00150 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.002) |
| Constant | 0.00239*** | | | 0.0121** | | |
| | (0.000) | | | (0.004) | | |
| Observations | 8496076 | 8484454 | 6539974 | 215497 | 215203 | 162491 |
| First-stage F-stat | | 8805.3 | 3765.8 | | 551.1 | 162.3 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A47: Wind direction IV and thermal inversion IV estimates of effect of NO2 and O3 on health care expenditure

| | Tot. spending 70 biggest cities[a] | Tot. spending entire France | | |
|---|---|---|---|---|
| | Wind dir. IV | Therm. inv. IV[b] | Therm. inv. IV[c] | Therm. inv. IV[d] |
| NO2 mean | 165.9*** | 0.662 | 9.424*** | 15.26 |
| | (2.587) | (0.579) | (0.757) | (9.096) |
| O3 mean | 92.97*** | -0.0556 | 4.004*** | 6.684 |
| | (3.183) | (0.115) | (0.443) | (4.169) |
| Observations | 215497 | 8490140 | 8490140 | 8490140 |
| First-stage F-stat | 389.4 | 5444.7 | 6361.0 | 7724.5 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis.
[a] Regression run on the sample of the 70 biggest cities due to computing power issues. This model includes a vector of temperature and precipitation bins and day of the week, month, year, and postcode fixed effects.
[b] Regression instruments for NO2 pollution only while O3 pollution is added as control.
[c] Regression instruments for O3 pollution only while NO2 pollution is added as control.
[d] Regression instruments simultaneously for NO2 and O3 pollution using the indicator variable for thermal inversion and its lag to have a suitable amount of instruments.
Models using thermal inversion as instrument include a vector of temperature and precipitation bins and day of the week, department by month, month by year, and postcode fixed effects.

# Les effets d'événements majeurs de la vie et de l'exposition à des conditions environnementales défavorables sur la santé et les résultats liés à la santé

Julia Mink

# Résumé

Nos expériences de vie et les conditions environnementales générales auxquelles nous sommes exposés façonnent notre esprit et notre corps. Il est essentiel de comprendre comment les événements majeurs de la vie et les conditions environnementales affectent notre comportement et influencent notre bien-être général, car ces connaissances peuvent être utilisées pour améliorer nos vies. Pourtant, l'estimation des effets causaux de ces événements et conditions sur tout résultat d'intérêt est difficile en raison de problèmes d'endogénéité et, bien souvent, d'un manque de données adéquates. De nombreuses études dans la littérature estiment des corrélations plutôt que des relations causales. Un grand nombre d'études existantes sont basées sur des analyses transversales, souvent sans inclure un groupe de contrôle adéquat et sans informations suffisantes sur les facteurs de confusion importants tels que les caractéristiques individuelles et familiales, ce qui entraîne des estimations potentiellement biaisées. Même lorsque des données de panel sont utilisées, de nombreuses études ne tiennent pas rigoureusement compte de la possibilité que des variables non-observées puissent affecter à la fois la variable de résultat et la probabilité d'exposition à l'événement ou à la condition, ce qui peut encore entraîner un biais dans les estimations. Compte tenu de ce biais potentiel dans les effets estimés, ces études corrélationnelles ont une valeur informative limitée.

L'objectif de cette thèse est de s'approcher le plus possible de l'établissement d'une *relation causale* entre l'exposition à certains événements de vie ou conditions environnementales et les résultats de santé ou, plus généralement, les résultats liés à la santé. À cette fin, j'applique une série de méthodes quasi-expérimentales et je m'appuie sur diverses sources de microdonnées provenant de France. Chacun des quatre chapitres qui composent cette thèse est un travail de recherche autonome et indépendant qui aborde des questions des questions distinctes et pertinentes pour les politiques publiques. Dans les deux premiers chapitres, j'examine l'impact de la retraite et de la séparation du couple, respectivement, sur le revenu et le régime alimentaire et je discute des effets potentiels de ces changements sur la santé. Dans le troisième chapitre, j'étudie les conséquences de l'exposition à des condi-

tions défavorables liées à la Seconde Guerre mondiale pendant l'enfance et l'adolescence sur la santé à l'âge adulte. Dans le quatrième chapitre, j'examine les effets à court terme de l'exposition à la pollution de l'air ambiant sur l'utilisation et les coûts des soins de santé.

La connaissance de l'impact des événements clés de la vie sur la santé et les résultats liés à la santé est cruciale pour les considérations de politique publique. L'étude de la retraite est particulièrement pertinente dans le contexte actuel de vieillissement des populations (United Nations, 2017). La proportion d'individus âgés de 60 ans ou plus en Europe devrait atteindre 35% d'ici 2050. Il a été démontré qu'une nutrition adéquate est importante pour éviter ou retarder l'apparition de certaines maladies chroniques liées à l'alimentation et le déclin cognitif, ainsi que des conditions telles que la fragilité chez les personnes âgées (World Health Organization, 2015). Les politiques de santé visant à éviter ou à retarder l'apparition de maladies chroniques et la dépendance aux soins pourraient non seulement améliorer le bien-être des personnes âgées concernées, mais aussi contribuer à réduire les coûts des systèmes de soins de santé déjà mis à rude épreuve. Une mesure correcte de l'impact du passage à la retraite sur les régimes alimentaires et la santé est utile pour orienter les décideurs politiques dans la conception et le ciblage de telles politiques de santé.

Le nombre important et croissant de personnes touchées par la dissolution d'une relation amoureuse rend l'étude de cet événement de vie également très pertinente d'un point de vue politique. En France, la part des couples cohabitants ayant rompu leur première union avant huit ans de vie commune a plus que doublé, passant de 12% pour les unions formées entre 1970 et 1978 à 29% pour celles formées entre 1997 et 2005. Les données transversales montrent que le niveau de vie moyen par personne des familles monoparentales est inférieur d'un tiers à celui des autres familles. Cela a des implications importantes pour les politiques publiques, étant donné que des ressources économiques inférieures sont associées à des résultats plus mauvais pour les adultes et les enfants, notamment une moins bonne santé psychologique et physique, des résultats scolaires plus faibles et davantage de problèmes de comportement (Amato, 2000, 2014; McLanahan et al., 2013; Tach and Eads, 2015). Des politiques bien ciblées soutenant les familles vulnérables de façon transitoire sont susceptibles d'éviter des résultats négatifs coûteux à l'avenir, mais nécessitent des informations adéquates sur la façon et le moment précis où les familles sont affectées. Cependant, la majorité des études sur les effets de la retraite ou de la composition du ménage sur les résultats économiques et la santé établissent des associations plutôt que des liens de causalité, ce qui limite leur valeur informative pour les recommandations politiques.

L'exposition à des expériences et à des conditions environnementales particulières in-

fluence le développement de la santé à tous les stades de la vie, mais il a été démontré que l'exposition pendant l'enfance et l'adolescence a des conséquences particulièrement puissantes et durables en raison de la persistance des attributs biocomportementaux acquis tôt dans la vie (Almond and Currie, 2011; Baird et al., 2017; Cunha and Heckman, 2007; Fall and Kumaran, 2019; Halfon and Hochstein, 2002; Hertzman, 1999). L'exposition à des conditions défavorables extrêmes telles que les privations liées à la guerre est susceptible d'avoir des effets dévastateurs et potentiellement durables sur la santé des enfants qui grandissent en temps de guerre. Pourtant, il n'y a eu que peu de recherches sur la façon dont l'exposition à la guerre au début de la vie affecte les résultats de santé à long terme dans la population civile. Une meilleure compréhension de l'impact des conditions de l'enfance sur les résultats de santé à l'âge adulte ouvre des perspectives en matière de prévention, de diagnostic et d'intervention.

Enfin, mon étude des effets de la pollution de l'air ambiant sur la santé est motivée par le fait que la pollution de l'air constitue le risque environnemental le plus important pour la santé des Européens (EEA, 2020). Il est souvent avancé que les normes de qualité de l'air sont fixées de manière quelque peu arbitraire, avec des preuves peu concluantes des avantages pour la santé et une prise en compte inadéquate des coûts supportés par les producteurs et les consommateurs. L'hétérogénéité potentielle des effets est rarement explorée de manière systématique. Des informations précises sur les avantages de la réduction de la pollution de l'air sont essentielles pour déterminer le niveau optimal de la politique environnementale, en particulier dans les cas où les niveaux de pollution sont déjà relativement bas, et où de nouvelles réductions de la pollution sont susceptibles d'être coûteuses. J'estime les effets causaux de la pollution atmosphérique sur l'utilisation et les coûts des soins de santé en France, où les niveaux de pollution sont en moyenne inférieurs aux valeurs limites actuelles.

Les contributions exactes de cette thèse à la littérature existante diffèrent selon l'événement de vie ou les conditions environnementales en question et sont détaillées dans le résumé suivant des chapitres de la thèse.

# Chapitre 1 : Évolution des achats alimentaires à la retraite en France

Le premier chapitre de cette thèse est co-écrit avec Olivier Allais et Pascal Leroy et a été publié dans *Food Policy.* (2020)[1]. Dans ce chapitre, nous étudions les effets de la retraite sur la consommation alimentaire et la nutrition en France.

Des recherches antérieures montrent que les ménages réduisent considérablement leurs dépenses alimentaires au moment de la retraite (Haider and Stephens, 2007; Fisher et al., 2008; Hurst, 2008; Battistin et al., 2009; Miniaci et al., 2010; Aguila et al., 2011; Barrett and Brzozowski, 2012; Luengo-Prado and Sevilla, 2013; Moreau and Stancanelli, 2015; Li et al., 2015; Stephens and Toohey, 2018). Ce résultat a été appelé "puzzle de la consommation (alimentaire) à la retraite" (*"retirement (food) consumption puzzle"*) car il contredit les implications du modèle de consommation standard du cycle de vie, qui prévoit que les agents prévoyants lissent leur consommation tout au long de leur vie afin d'éviter les fluctuations induites par des changements de revenus prévisibles tels que la réduction des revenus à la retraite (Friedman, 1957; Modigliani and Brumberg, 1980). Cependant, la diminution des dépenses alimentaires n'indique pas nécessairement que les quantités consommées varient dans la même mesure. Les ménages peuvent dépenser moins pour l'alimentation mais maintenir la quantité totale d'aliments consommés en ajustant leurs choix en matière de qualité et de variétés d'aliments achetés. Après la retraite, les ménages nouvellement pauvres en argent mais riches en temps peuvent consacrer plus de temps à faire les courses et préparer à la maison des repas qui prennent du temps mais qui sont moins chers (Hurst, 2008; Stancanelli and Van Soest, 2012). Des preuves empiriques de cette théorie ont été présentées dans Aguiar and Hurst (2005) pour les États-Unis et dans Chen et al. (2017) et Dong and Yang (2017) pour la Chine. Pourtant, les travaux récents de Stephens and Toohey (2018), qui ont reproduit et étendu l'étude influente de Aguiar and Hurst (2005), ont remis en cause ces résultats, en constatant que l'apport calorique et nutritionnel diminue à la retraite.

Nous contribuons à ce débat en cours sur le "puzzle de la consommation (alimentaire) à la retraite" en évaluant l'impact de la retraite sur la consommation alimentaire à la fois en termes de dépenses alimentaires et de quantités réelles achetées. Nous utilisons des données détaillées sur l'ensemble des produits alimentaires achetés par un panel représentatif de ménages français provenant de *Kantar Worldpanel* couvrant la période 2005 à 2014. Ex-

[1] doi.org/10.1016/j.foodpol.2019.101806

ploitant l'aspect longitudinal des données, nous mettons en œuvre un modèle à effet fixe du ménage qui nous permet de contrôler les caractéristiques du ménage *invariantes dans le temps*. Avec Stephens and Toohey (2018), notre étude est l'une des premières à utiliser des données longitudinales pour étudier plus rigoureusement l'impact de la retraite sur la consommation alimentaire. Nous envisageons en outre la possibilité que nos estimations soient encore biaisées si des caractéristiques des ménages *variants dans le temps* sont corrélées avec le statut de retraité et la consommation alimentaire. Nous abordons ce problème d'endogénéité en utilisant l'âge minimum légal de la retraite comme instrument pour le statut de retraité. La stratégie d'identification repose sur le fait que d'atteindre l'âge minimum légal de la retraite, et donc de devenir éligible aux prestations de retraite, a une forte influence sur la décision de l'individu de prendre sa retraite (Diamond and Gruber, 1999). Cette incitation discontinue dans les régimes de retraite constitue un choc exogène sur le comportement de départ à la retraite que nous exploitons pour estimer l'impact causal de la retraite sur les achats alimentaires.

En plus d'étudier les dépenses alimentaires et les quantités achetées globales, nous divisons les produits alimentaires en 6 groupes, en considérant les similitudes dans le contenu nutritionnel et les préférences des consommateurs. La définition de ces groupes alimentaires est utile pour étudier l'évolution des habitudes alimentaires au moment de la retraite. Comme la composition nutritionnelle des aliments diffère d'un groupe alimentaire à l'autre, les changements relatifs des quantités achetées dans ces groupes impliquent des changements différents dans les apports en nutriments. Il est utile de savoir comment les apports en nutriments varient pour en déduire les effets sur la santé. À ma connaissance, il n'existe pas d'étude existante utilisant des données européennes qui examine l'impact causal de la retraite sur l'ensemble du régime alimentaire au niveau des catégories d'aliments.

Nous constatons que les ménages diminuent sensiblement leurs dépenses alimentaires et la quantité de nourriture achetée au moment de la retraite et que la baisse des dépenses est à peu près proportionnelle à la baisse des quantités achetées. En supposant que les ménages consomment ce qu'ils achètent, cela suggère que la retraite ne conduit pas seulement les ménages à dépenser moins d'argent pour l'alimentation mais qu'ils consomment également une plus petite quantité de nourriture. Cela va à l'encontre de l'hypothèse selon laquelle les retraités modifient leur comportement d'achat sans réduire leur consommation alimentaire réelle. Nos résultats prouvent l'existence du "puzzle de la consommation (alimentaire) des retraités". En outre, nous constatons des baisses plus importantes des achats alimentaires dans les ménages dont le revenu avant la retraite est plus faible, ce qui suggère que l'épargne et les ressources du système de protection sociale de ces ménages ne leur permettent pas

de lisser leur consommation à la retraite. Cela indique des pertes de bien-être qui peuvent être traitées par une intervention politique appropriée. Enfin, nos résultats indiquent que la diminution des achats alimentaires que nous constatons au niveau global est due à une baisse des achats de produits alimentaires d'origine animale. Il en résulte une réduction de l'apport en acides gras saturés et en sel, ce qui peut avoir des effets positifs sur la santé, mais aussi une réduction de l'apport en nutriments favorables à la santé tels que les protéines, le calcium et les vitamines.

## Chapitre 2 : Foyers brisés et garde-manger vides : L'impact de la séparation du couple sur sur les ressources économiques des ménages

Dans ce chapitre, j'étudie l'impact de la séparation du couple sur les ressources économiques du ménage en étudiant les changements dans les revenus et les achats alimentaires autour du moment de la rupture dans un panel de ménages français. Pour déduire les effets potentiels sur la santé, j'examine les changements par groupe d'aliments pour suivre les habitudes alimentaires et évaluer si ces changements se traduisent par des modifications du poids corporel des membres du ménage.

Les conséquences économiques de la dissolution d'une union ont été étudiées à de nombreuses reprises, mettant en évidence une baisse de revenu un an après un divorce allant de 23% à 40% (Hoffman, 1977; Duncan and Hoffman, 1985b; Bianchi and McArthur, 1991; Holden and Smock, 1991; McLanahan and Sandefur, 1994; Peterson, 1996; Galarneau and Sturrock, 1997; McKeever and Wolfinger, 2001; Avellar and Smock, 2005; Tach and Eads, 2015). Dans la plupart des études, les effets ont été estimés en comparant les changements sur deux périodes, avant et après la rupture. Cependant, les estimations basées sur de simples comparaisons "avant et après" sont susceptibles d'être biaisées si l'effet n'est pas immédiat et constant dans le temps. En outre, bon nombre de ces études ne comportent pas de groupe de contrôle. En ce qui concerne les habitudes alimentaires, quelques études examinent les associations entre les changements de l'état matrimonial et les comportements alimentaires, en se concentrant sur un ensemble limité d'aliments (Lee et al., 2004; Vinther et al., 2016).

J'utilise les données d'un panel de ménages français provenant de *Kantar Worldpanel* pour étudier l'impact de la séparation du couple sur le revenu du ménage et les achats ali-

mentaires en tant qu'indicateurs des ressources économiques du ménage. J'estime un modèle à effets fixes du ménage pour tenir compte des caractéristiques inobservées du ménage variant dans le temps, en plus d'inclure des covariables variant dans le temps telles que la situation professionnelle des deux conjoints. J'examine les changements dans le revenu et les achats de nourriture dans les années avant, pendant et après la rupture par rapport à une période de référence de trois ans ou plus avant l'événement pour tenir compte de la possibilité d'ajustements au fil du temps aux changements dans le statut de la relation.

Je n'ai connaissance d'aucune étude portant sur l'évolution dans le temps des revenus et de l'alimentation après la séparation du couple en France. Les ajustements dynamiques aux changements de statut de la relation sont rarement étudiés car les données longitudinales nécessaires sur un grand nombre représentatif de ménages ne sont pas facilement disponibles. Quelques rares études ont utilisé des données longitudinales pour étudier l'évolution dans le temps du revenu et de la consommation après une séparation, mais elles n'ont pas contrôlé les caractéristiques du ménage qui varient dans le temps ou ne tiennent pas compte de l'hétérogénéité non observée (Fisher and Low, 2016; De Vaus et al., 2014, 2017; Fisher and Low, 2009). Une exception notable est une étude de Page and Stevens (2004) utilisant des données américaines dans laquelle les changements dans le revenu du ménage et les dépenses alimentaires après la séparation du couple sont estimés à l'aide de modèles à effet fixe du ménage et de contrôles pour des covariables supplémentaires variant dans le temps. Contrairement à toutes les recherches précédentes dont j'ai connaissance, j'examine en outre si les changements dans les achats alimentaires entraînent des changements dans le poids corporel des membres du ménage ou des changements dans la qualité de leur régime alimentaire en termes de part de produits alimentaires malsains achetés.

Je constate que le revenu du ménage et les achats alimentaires diminuent de façon soudaine et significative au moment de la séparation du couple et restent inférieurs pendant plusieurs années après la rupture. La diminution des achats alimentaires semble entraîner une légère baisse du poids corporel des femmes nouvellement célibataires. Je constate également que la part des achats d'aliments malsains augmente au moment de la séparation, ce qui suggère que les ménages adoptent des régimes alimentaires moins équilibrés. Si une réduction de poids peut avoir des effets bénéfiques sur la santé, l'adoption de régimes alimentaires moins équilibrés est susceptible d'avoir des conséquences négatives sur la santé. Mes résultats indiquent que les ménages à faible revenu sont particulièrement vulnérables car ils semblent moins en mesure de lisser leur consommation : Alors que la baisse du revenu est plus prononcée pour les ménages dont le revenu avant séparation est plus élevé, je constate que la baisse des achats alimentaires et du poids corporel touche principalement les ménages

dont le revenu avant séparation se situe dans le tercile inférieur. Si nous supposons que les préférences en matière de perte de poids ou l'incidence de la dépression liée à la séparation ne diffèrent pas d'un ménage à l'autre en fonction du niveau de revenu avant la séparation, le fait de constater des baisses plus importantes des achats de nourriture et du poids du partenaire féminin dans le tercile le plus pauvre des ménages mais pas dans le tercile le plus riche suggère que ces changements sont dus à des ressources financières insuffisantes.

Mes résultats soulignent l'importance d'étudier non seulement le revenu des ménages mais aussi leur consommation pour déterminer quels sont les ménages particulièrement vulnérables aux difficultés économiques après la séparation du couple. L'évolution des achats alimentaires est sans doute une mesure plus directe de l'évolution des ressources économiques que l'évolution des revenus, car les achats alimentaires renseignent sur la capacité d'un ménage à maintenir un certain niveau de dépenses nécessaires.

## Chapitre 3 : Les effets à long terme de la guerre sur la santé : Les données de la Seconde Guerre mondiale en France

Le troisième chapitre de cette thèse explore les effets de l'exposition à la Seconde Guerre mondiale pendant l'enfance et l'adolescence sur la santé à l'âge adulte. Ce chapitre est co-écrit avec Olivier Allais et Guy Fagherazzi et a été publié dans *Social Science & Medicine* (2021)[2].

Bien que l'exposition à des environnements et expériences particuliers semble influencer le développement de la santé à toutes les étapes de la vie, il a été suggéré que l'exposition à des facteurs de stress pendant l'enfance et l'adolescence a des conséquences particulièrement puissantes et durables sur la santé en raison de la persistance des attributs bio-comportementaux acquis tôt dans la vie. De nombreuses études examinent la relation entre les conditions de vie au début de la vie et la santé à l'âge adulte en utilisant comme expérience naturelle des cohortes exposées à des événements historiques. Plusieurs articles ont été écrits sur l'impact de l'exposition à la Seconde Guerre mondiale, principalement sur l'effet de la famine liée à la guerre. Cependant, la plupart de ces études trouvent des associations (non causales) (Elias et al., 2004, 2005; Dirx et al., 1999, 2001; van den Brandt et al., 2002; Portrait et al., 2011;

[2] https://doi.org/10.1016/j.socscimed.2021.113812

Koupil et al., 2007; Sparén et al., 2004; Havari and Peracchi, 2017).

Nous utilisons les données de l'étude de cohorte prospective française E3N sur plus de 28,000 femmes employées dans l'Education Nationale française (principalement des enseignantes) nées entre 1925 et 1950. Nous combinons ces données démographiques et sanitaires avec des données historiques sur les morts militaires françaises, les prisonniers de guerre français et les bombardements alliés sur la France pendant la Seconde Guerre mondiale. Contrairement à la plupart des études existantes qui reposent sur des résultats de santé autodéclarés, nous utilisons des données sur l'incidence objectivement mesurée du cancer, de l'hypertension, de l'angine, de l'infarctus du myocarde, du diabète et de l'obésité. Nous sommes également en mesure de distinguer les effets de l'exposition aux difficultés liées à la guerre, telles qu'elles sont saisies par nos mesures de la guerre basées sur les données historiques, des effets des pénuries nutritionnelles, car nous disposons d'informations sur le niveau de la faim subie pendant la Seconde Guerre mondiale, tel que rapporté par les participants à l'étude.

Pour établir la causalité, nous exploitons la variation de l'intensité de la guerre dans le temps et l'espace, qui est plausiblement exogène aux caractéristiques individuelles et familiales. Nous comparons les résultats de santé des femmes nées dans des zones de code postal qui ont été intensément touchées par la guerre avec ceux des femmes appartenant au même groupe de cohortes de naissance mais qui sont nées dans des zones de code postal moins touchées, par rapport aux femmes des autres cohortes de naissance. Les stratégies d'identification de ce type sont souvent utilisées dans la littérature quasi-expérimentale mais l'exploitation de données à un niveau géographique aussi fin que la zone du code postal est moins courante. Notre travail est le plus proche de celui de Akbulut-Yuksel (2017) qui utilise également des données à un niveau géographique fin et emploie une stratégie d'identification similaire pour étudier les effets de l'exposition pendant l'enfance aux bombardements alliés sur la santé des adultes en Allemagne. Une réserve importante de cette étude, cependant, est qu'elle exploite des données sur la résidence à l'âge adulte et non le lieu de naissance, ce qui est susceptible de compromettre la stratégie d'identification. Quelques autres études utilisent des stratégies d'identification similaires à un niveau géographique fin mais avec un objectif différent. Par exemple, Schiman et al. (2019) n'étudient pas les effets de la guerre, mais plutôt l'augmentation de la mortalité infantile induite par la guerre, tandis que Conti et al. (2019) se concentrent sur l'exposition prénatale.

Nous constatons qu'une augmentation de l'intensité de l'exposition à la guerre de la Seconde Guerre mondiale, mesurée par le nombre de victimes militaires françaises dans

la zone de code postal de naissance des femmes, entraîne une détérioration de la santé à l'âge adulte pour celles qui ont été exposées au cours des cinq premières années de leur vie. Les résultats sont robustes à l'inclusion des comportements observés affectant la santé (consommation de tabac, durée du sommeil et alimentation), ce qui suggère que les effets ne sont pas médiatisés par des changements dans ces comportements de santé. Nos résultats restent également inchangés lorsque nous contrôlons le niveau de faim souffert pendant la Seconde Guerre mondiale, tel que rapporté par les participants à l'étude, ce qui indique que les effets que nous capturons à travers nos mesures de l'exposition à la guerre sont distincts des effets des pénuries nutritionnelles liées à la guerre.

Les résultats de notre étude suggèrent que les effets de la guerre sur certaines formes de capital humain sont durables, ce qui contraste avec les effets de la guerre sur le capital physique, qui se sont avérés relativement courts (Bellows and Miguel, 2009; Brakman et al., 2004; Davis and Weinstein, 2002; Miguel and Roland, 2011). Le fait que nous ne trouvions des effets que chez les personnes exposées pendant les cinq premières années de la vie suggère qu'il existe une période critique ou sensible du développement pendant laquelle les individus sont plus vulnérables aux expériences négatives. L'existence de périodes critiques ou sensibles est encore très débattue dans la littérature et nos résultats contribuent à ce débat en fournissant de nouvelles preuves empiriques. Nos résultats soulignent l'importance des politiques post-conflit ciblant principalement les enfants exposés pendant la petite enfance afin d'atténuer, voire d'inverser, les effets négatifs à long terme sur la santé causés par l'exposition à la guerre.

## Chapitre 4 : Donner un prix à la pollution atmosphérique : les coûts de la pollution de l'air pour le système de santé en France

Dans le dernier chapitre de cette thèse, j'étudie les effets de la pollution atmosphérique sur l'utilisation et les coûts des soins de santé en France. Ce chapitre est mon document de travail le plus récent et mon "job market paper".

L'exposition à la pollution atmosphérique a des effets néfastes bien documentés sur la santé humaine, comme un risque accru de maladies cardiovasculaires et respiratoires et de cancers. En 2016, on estimait que la pollution atmosphérique contribuait à 7,6% des décès dans le monde (WHO, 2017). En réaction, de nombreux pays ont mis en place des

normes et des objectifs de qualité de l'air pour un certain nombre de polluants présents dans l'air. Pourtant, il est souvent avancé que ces normes sont fixées de manière arbitraire, sans preuve concluante des avantages pour la santé à mettre en balance avec les coûts de la réduction de la pollution pour les producteurs et les consommateurs. Des informations précises sur les avantages d'une réduction de la pollution atmosphérique sont très importantes pour déterminer le niveau optimal de la politique environnementale, en particulier dans le contexte des pays développés où les niveaux de pollution sont déjà relativement bas et où de nouvelles réductions de la pollution risquent d'être coûteuses. J'estime les effets causaux de la pollution de l'air sur l'utilisation et les coûts des soins de santé en France, où les niveaux de pollution sont pour la plupart situés en dessous des valeurs limites actuelles.

L'estimation de l'effet causal de la pollution atmosphérique sur les coûts des soins de santé est difficile en raison des problèmes d'endogénéité et d'un manque général de données adéquates. Au cours de la dernière décennie, les chercheurs ont utilisé des plans quasi-expérimentaux qui utilisent une source exogène plausible de variation de la pollution pour estimer les effets causaux de la pollution atmosphérique sur la santé. Cependant, ces études se limitent généralement à des zones géographiques et des périodes relativement étroites, ne prennent en compte qu'une partie spécifique de la population - le plus souvent les enfants ou les personnes âgées - ou étudient les effets de la pollution sur une sélection limitée de conditions de santé (Anderson, 2015; Schlenker and Walker, 2015; Knittel et al., 2016; Arceo et al., 2016; Deryugina et al., 2016; Schwartz et al., 2016; Ebenstein et al., 2016; Deschênes et al., 2017; Bauernschuster et al., 2017; Deryugina et al., 2019; Godzinski and Suarez Castillo, 2019). La plupart des travaux existants portent sur la mortalité, un événement plutôt extrême qui est moins susceptible de se produire après une exposition à des niveaux modérés de pollution.

À ma connaissance, il s'agit de la première étude quasi-expérimentale visant à quantifier de manière exhaustive les coûts des soins de santé causés par l'exposition à des niveaux modérés de pollution atmosphérique dans un échantillon représentatif à l'échelle nationale. Je combine des données administratives uniques sur les remboursements de soins de santé pour un échantillon représentatif de la population française à fréquence quotidienne avec des données spatiales sur les niveaux de pollution et les conditions météorologiques, et des données collectées manuellement sur les grèves des transports publics. J'adopte une approche de variable instrumentale (IV) où j'utilise comme IV la variation quotidienne de l'intensité de la pollution atmosphérique au niveau de la zone de code postal induite par la variation de la vitesse et de la direction du vent et les périodes de grève dans le secteur des transports publics. L'hypothèse d'identification est que la variation de la pollution due aux changements

de la vitesse et de la direction du vent ou aux grèves des transports publics n'est pas liée aux changements de l'utilisation ou des coûts des soins de santé, sauf par l'influence sur la pollution atmosphérique. Cela devrait être le cas après avoir contrôlé de manière flexible divers effets fixes de temps et de lieu et plusieurs covariables supplémentaires telles que les conditions climatiques. Il est peu probable que la direction du vent et les niveaux communs de vitesse du vent aient un effet direct sur l'utilisation des soins de santé autrement que par l'effet sur la pollution atmosphérique. Je ne trouve pas de preuve d'une augmentation de l'utilisation des soins de santé les jours où la vitesse du vent est élevée. En ce qui concerne les grèves du secteur public, la restriction d'exclusion devrait être valable au moins pour certaines spécialités médicales telles que les soins cardio-vasculaires et respiratoires, que je peux analyser séparément.

J'estime qu'une augmentation de 1µg/m3 des concentrations journalières de NO2 et O3 se traduit par une augmentation des dépenses de santé équivalente à €2,5 milliards par an. Ces estimations ne reflètent que les coûts de l'exposition à court terme à la pollution atmosphérique, les effets potentiellement encore plus importants de l'exposition à long terme n'étant pas pris en compte. Pourtant, ces coûts élevés liés à la seule exposition à court terme suggèrent qu'il y a des avantages considérables à réduire la pollution atmosphérique encore davantage en dessous des valeurs limites actuelles. Mes estimations de coûts sont supérieures de plusieurs ordres de grandeur aux estimations des études coûts-bénéfices (voir par exemple Fontaine et al. (2007); Rafenberg (2015); Pimpin et al. (2018)). Bien que ces études indiquent clairement que leurs estimations des coûts des soins de santé sont prudentes, on ignore dans quelle mesure les effets totaux ont été sous-estimés. Mes estimations permettent de mettre en perspective à quel point les coûts totaux des soins de santé ont été sous-estimés à ce jour.

L'étude fournit également des preuves d'une hétérogénéité significative des effets selon les caractéristiques des patients et des lieux. Par exemple, les effets de l'augmentation de la pollution par les NO2 et les O3 sur les dépenses de santé sont 4 à 6 fois plus forts dans les zones de codes postaux les plus inégales que l'effet dans les zones de codes postaux les plus égales (tel que mesuré par l'Indice de Gini). Cela suggère que les politiques de réduction de la pollution atmosphérique ont le potentiel de réduire les inégalités en matière de santé.

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